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# Cloudy Judgments: The Timing of Weather-Induced Biases*

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**Abstract**

Households making economic decisions involving durable goods need to evaluate future value and utility. While behavioral biases are known to affect such choices, it remains unclear when in the decision process they arise. Using high-frequency housing market data, we examine how transient environmental factors shape expectations. We find that cloud cover during the open house stage significantly reduces sales prices, while cloud cover during the bidding stage has no effect. This effect is not driven by attendance at open houses or by the number of bidders, highlighting the role of early-stage perceptions even under strong incentives for rationality.

**Keywords**: Weather; Behavioral biases; Price formation; Housing market; Mood; Salience
**JEL codes**: D84; G12; G14; G41; R21; R31

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# 1 Introduction

Households purchasing durable goods need to assess value and utility across future states of the world. Behavioral economics has shown that such intertemporal judgments are prone to systematic distortions, including projection bias, present bias, and salience effects (e.g., Loewenstein et al., 2003; DellaVigna, 2009; Bordalo et al., 2012, 2013). These biases have been documented across diverse contexts (see below), although evidence remains scarce for large-scale investment decisions, which may provide stronger incentives for rationality.

More fundamentally, we do not yet understand *when* such behavioral biases exert their influence. The purchase of durable goods such as cars or houses typically unfolds in multiple stages. Prospective buyers often engage in information gathering and evaluate the good through direct interaction—e.g., test-driving a car or visiting a home—before a purchase decision is made. Do behavioral biases arise early in the decision-making process when individuals form first impressions and encode information, or do they emerge later, during deliberation, during the heat of a bidding process, or a final commitment? This distinction has both conceptual and practical implications. Economic models often assume stable preferences and expectations throughout the decision process. However, if momentary cues, such as weather-induced mood or visual salience, shape early-stage value assessments or attention, models of decision making may improve their explanatory power by explicitly modeling those stages, and help better understand buyer behavior. The timing question is difficult to answer because researchers typically only observe the outcome of a decision—e.g., the purchase of a good, the submission of an offer, or the execution of a trade, but not earlier stages during which expectations about future utility are formed.

In this paper, we address this question in the context of residential real estate, using high-frequency administrative data from Norway. Specifically, we examine at which stage of decision making weather affects home prices. Our empirical setting offers a unique advantage: in the Norwegian housing market, homes are listed online approximately ten days before the open house. Crucially, listings announce the dates of open house(s) and auction. This institutional structure means sellers cannot strategically time open houses to coincide with sunny weather. This allows us to isolate exogenous variation in weather on the days buyers physically visit properties from weather on the day of the auction: the open houses are followed a few days later by an online auction with legally binding bids, and a home is sold at the instant the seller accepts a bid. This structure enables us to cleanly separate the timing of the first in-person exposure to a home (the open house) from the moment of commitment to purchase (the auction). Hence, we can observe weather variation at each of these stages and identify when behavioral effects occur.

Our main finding is that cloud cover during the open house stage reduces transaction prices, whereas cloud cover during the auction has no measurable effect. In our preferred model specification using repeat sales data with housing unit fixed effects and controlling for seasonality and an array of weather variables and interaction effects, a one standard deviation increase in cloud cover from the mean during the open house reduces home prices by 0.85% (p-value$<$0.05), at the sample means, corresponding to $2,982 for the median home in our sample. This effect corresponds to a 7.50% hypothetical increase in the mortgage rate during our time period (2015-2021). Results are qualitatively robust to a series of alternative specifications, including measures of sunshine instead of cloud cover, inclusion of alternative fixed effects, and sample choices. A placebo test with random draws of weather conditions indicates no economically meaningful effect of cloud cover. These results suggest that buyers' initial in-person impressions are affected by transient cues like cloud cover, consistent with behavioral channels such as attribute salience and projection bias. Buyers appear to overweight visually salient or mood-congruent features during the initial in-person evaluation of the asset. For instance, sunshine may draw attention to attractive features like views, natural light, or terraces that may feel more inviting, inflating perceived value even if underlying fundamentals remain unchanged. Buyers appear to overweight visually salient or mood-congruent features during the initial in-person evaluation of the asset. For instance, sunshine may draw attention to attractive features like views, natural light, or terraces that may feel more inviting, inflating perceived value even if underlying fundamentals remain unchanged.

We consider whether our findings can be explained by standard rational-agent models. We rule out several such channels. For example, we find no evidence that cloud cover reduces buyer turnout at open houses or participation in auctions—patterns one would expect if search frictions explained the main results in an otherwise rational model. Nor can sellers' strategic behavior explain the results, since open houses are scheduled well in advance. We further explore mechanisms underlying our main findings. Effects are stronger for apartments, which generally lack outdoor features enhanced by sunlight. This finding is inconsistent with the rational idea that the positive evaluation of outdoor features is only possible during good weather, but consistent with behavioral biases. Moreover, if good weather induced projection bias, as in Conlin et al. (2007), we would expect weather effects both during open houses and during the bidding process—which we do not. This suggests that attribute salience rather than projection bias is the dominant mechanism. If mood is what causes the bias, it is mood during first impressions rather than during the bidding process.

These findings are the first in the literature to provide evidence on the *timing* of weather-induced behavioral effects in economic decision-making. Previous work documents that weather affects decision making in financial markets (e.g., Saunders, 1993; Hirshleifer and Shumway, 2003; Goetzmann and Zhu, 2005; Tunyi and Machokoto, 2021), consumer spending (Murray et al., 2010), college enrollment (Simonsohn, 2010), solar panel adoption (e.g., Lamp, 2023), crime (Cohn, 1990), catalog orders (Conlin et al., 2007), and outdoor movie ticket sales (Buchheim and Kolaska, 2017). In particular, Busse et al. (2015) document that convertible car purchases are more likely on sunny days or after periods of warm weather. In their setting, the day of the test drive is both a choice of the prospective buyer and not observable to the econometrician. Furthermore, in some durable goods markets (such as automobiles), in-person evaluations (such as test drives) may take place on the same day as the purchase, blurring the distinction between initial impressions and final decision. By contrast, the open house date in our setting is set well in advance, is observable, and is distinct from the auction date. Bonan et al. (2024) find that high temperatures are associated with reduced online search intensity for air conditioners, which may be a joint effect of retailer and customer behavior. In our setting, sellers cannot strategically time open houses to coincide with sunny weather. Gourley (2021) studies the effect of average temperature and precipitation in the month preceding the closing date on home prices in Colorado, but does not observe the weather on clearly defined open house or purchase days, and hence cannot address the question of *when* behavioral effects emerge in decision making.

More broadly, we inform a literature on decision-making under uncertainty and intertemporal choice. Our findings inform when weather-induced behavioral effects emerge and support theoretical models in which incidental context, such as mood or salience, shapes early cognition and attention allocation (Bordalo et al., 2013). Moreover, the literature showing that behavioral biases such as projection bias, salience, and misattribution of mood as informational cues, can distort valuation when utility is state-dependent or must be forecast, thus far often relies on lab experiments or smaller-stakes decisions (Loewenstein et al., 2003; DellaVigna, 2009; Bordalo et al., 2012, 2013). Our evidence contributes higher-stakes real-world decisions. This context is particularly important, as housing represents the largest financial asset for most households (Campbell and Cocco, 2007), implying stronger incentives for rational behavior and potentially less scope for behavioral biases.

The next section describes the data. Section 3 discusses the empirical framework. Section 4 presents the results. Section 5 explores potential mechanisms. Last, Section 6 concludes.

# 2 Data

## 2.1 Data and study sample

This section provides an overview of the data sources, variable construction, and the rationale behind the sample selection. Additional details are available in Appendix A.

Our analysis draws on data from multiple sources. First, we use listings and sales transaction data from Eiendomsverdi AS, covering the largest municipalities in the south-eastern region of Norway from 2015 to 2021. These data include the sale price (which incorporates any common debt, if applicable), property attributes, listing and sale dates, and zip code. Sale prices are deflated to 2015 levels using the consumer price index and converted to U.S. dollars (USD) using the NOK/USD exchange rate as of January 2, 2023 (9.8413). All transactions in our dataset are second-hand, on-market sales between private individuals. Norway has two main forms of property ownership: co-operative (co-op) and non-co-operative (non-co-op). Housing units fall into one of four categories: apartments, detached houses, semi-detached houses, and row houses.[1] Additional property attributes include living area and lot size, both measured in square meters.

Second, we obtain three weather-related datasets from the Copernicus Climate Change Service (Copernicus Climate Change Service, 2024a,c,b): (i) daily daytime cloud cover with a median grid cell size of 336 square kilometers, measured on a scale from 0 (clear sky) to 1 (completely overcast) (Karlsson et al., 2023); (ii) daily accumulated precipitation and maximum temperature at a 1×1 kilometer resolution (Tveito et al., 2000, 2005); and (iii) daily wind speed forecasts from the ERA5 model, with a median grid cell size of 100 square kilometers (Muñoz Sabater, 2019). To account for the potential role of daylight in how cloud cover is perceived, we construct a variable denoted as 'Hours of Night' (HoN), using an approach similar to that proposed by Kamstra et al. (2003). All weather and HoN variables are aggregated to the zip code level. Following Goetzmann et al. (2015), we create monthly, zip code-specific seasonal controls by averaging each weather variable across the full sample period (2013–2023) for each month from March through November. All weather and HoN variables, including their seasonal counterparts, are log-transformed using the natural logarithm.

Third, we obtain administrative data from Statistics Norway, including buyer characteristics and monthly aggregated mortgage rates reported by consumer banks. The buyer data cover the period 2014–2019 and include end-of-year measures of income, debt, and wealth, as well as information on household composition (number of adults and children),

[1] The key distinction between co-ops and non-co-ops lies in the ownership structure. In co-ops, individuals own their homes indirectly through a cooperative association. Both ownership types are common in cities, while non-co-ops dominate in rural regions.

household type, education level, age, and gender.

Fourth, we use a supplementary dataset from DNB Eiendom, Norway's second-largest real estate firm with a market share of approximately 20 percent. This dataset includes detailed information on housing transactions, the exact open house dates, and buyer interest between August 2018 and June 2023, including the number of open house attendees and the number of bidders participating in the online auction.

Our sample includes transactions from the 13 most populous municipalities in southeastern Norway, based on 2021 population figures (see Figure 1). Climatic conditions in Norway vary considerably by region—for example, the west coast is characterized by frequent wind and heavy precipitation, while the northern areas above the Arctic Circle experience colder temperatures and extreme seasonal variation in daylight. We focus on the southeastern region because it offers milder and more uniform weather patterns, making it well suited for our analysis and more representative of other housing markets. We exclude the winter season—defined as December through February—from our main analysis. This period accounts for only 17% of sales in our sample and is marked by limited daylight (averaging 7.12 hours in our study area, located between latitudes 58 and 60), reducing its comparability to other real estate markets.[2] In addition, winter-specific factors—such as snow cover and depth—may confound the relationship between cloud cover and housing prices.

## 2.2 Cloud cover during the different stages of the sales process

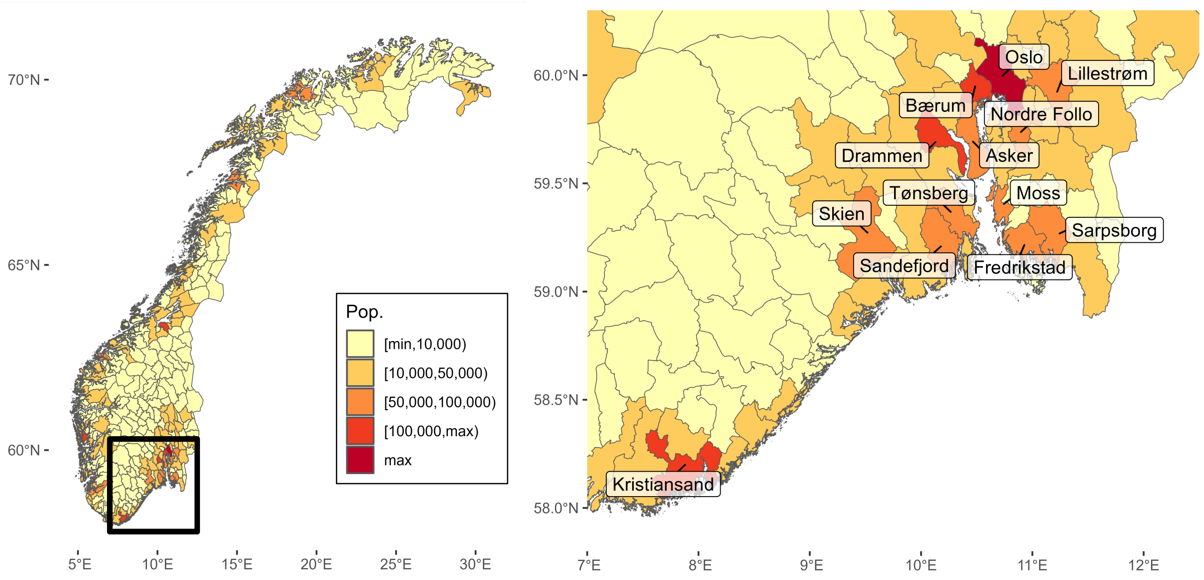
The sales process in the Norwegian housing market is highly standardized, which enables us to recover the day of the sale and infer the likely dates of the open houses relatively precisely. The sales process unfolds in three stages. First, the housing unit is listed online, with the open house and auction dates announced in the listing. Second, prospective buyers attend the open house(s). Third, bidding begins on the first working day after the final open house, and the unit is typically sold the same day.

Using our supplementary dataset with exact open house dates, we find that 79% of homes are sold the day after the *last* open house, and 85% are sold within four days of the *first* open house—even when conditioning on municipality (Figure A.2). To capture the effect of sunshine during the open house period, we measure cloud cover[3] and other weather variables as the moving average of the four days preceding the sale date—effectively lag-

[2]As a robustness check, we estimate the main model including all four seasons in Appendix D. As expected, the overall effects diminish due to added noise. When allowing all weather variables to have distinct slopes in winter, cloud cover during open houses has no impact on sale prices, while effects in the remaining seasons remain consistent with our main results.

[3]Using cloud cover as a proxy for sunshine is standard practice (see, e.g., Saunders, 1993; Hirshleifer and Shumway, 2003; Goetzmann and Zhu, 2005; Busse et al., 2015; Goetzmann et al., 2015). Results using direct measures of sunshine duration are consistent and presented in Appendix E.

Figure 1: Sample municipalities in the south-east of Norway




**Notes**: The figure shows the location of the municipalities in our sample and the 2021 population by municipality for Norway (left panel) and for the southeastern part of Norway with the names of the municipalities included in our sample (right panel).

ging the moving average by one day. (We discuss the rationale for using an unweighted average in Appendix A.)

To assess the impact of cloud cover during the final stage of the sales process—when bids are submitted in the auction—we measure cloud cover and other weather variables on the day of the sale. Summary statistics for both same-day weather (DOS) and the one-day-lagged moving averages are provided in Table 1.

# 3 Empirical framework

This section introduces two main specifications for estimating the effect of cloud cover-induced mood on housing market outcomes. We propose specifications to estimate the effect of cloud cover during open houses, and on the day of the sale, on sale prices.

Table 1: Summary statistics

| N = 55,823 | Mean | SD | 25th pct. | Median | 75th pct. |
|---|---|---|---|---|---|
| **Home sales** | | | | | |
| Sale price (in 1,000 USD) | 411.20 | 211.30 | 274.63 | 350.16 | 483.87 |
| Size (sqm.) | 88.18 | 47.20 | 55.00 | 73.00 | 109.00 |
| Age (years) | 52.12 | 36.84 | 27.00 | 49.00 | 67.00 |
| TOM (days) | 10.57 | 3.30 | 8.00 | 10.00 | 11.00 |
| Lot size (sqm.) | 2,001.20 | 9,853.77 | 437.00 | 744.00 | 1,068.00 |
| Apartments (share) | 0.70 | | | | |
| Non-co-op (share) | 0.60 | | | | |
| Mortgage rate | 2.40 | 0.41 | 2.22 | 2.45 | 2.62 |
| **Across seasons** | | | | | |
| Cloud cover (MA) | 0.59 | 0.25 | 0.42 | 0.61 | 0.78 |
| Precipitation (mm/day, MA) | 2.85 | 3.87 | 0.06 | 1.28 | 4.15 |
| Cloud cover (DOS) | 0.59 | 0.38 | 0.19 | 0.69 | 0.98 |
| Precipitation (mm/day, DOS) | 3.03 | 6.99 | 0.00 | 0.02 | 2.44 |
| Hours of night | 10.05 | 3.52 | 6.93 | 9.67 | 12.63 |
| **Spring** | | | | | |
| Cloud cover (MA) | 0.63 | 0.25 | 0.48 | 0.66 | 0.82 |
| Precipitation (mm/day, MA) | 2.14 | 2.84 | 0.02 | 0.82 | 3.39 |
| Cloud cover (DOS) | 0.59 | 0.39 | 0.18 | 0.71 | 1.00 |
| Precipitation (mm/day, DOS) | 1.96 | 4.75 | 0.00 | 0.00 | 1.29 |
| Hours of night | 9.39 | 2.40 | 7.27 | 9.02 | 11.62 |
| **Summer** | | | | | |
| Cloud cover (MA) | 0.51 | 0.23 | 0.36 | 0.52 | 0.69 |
| Precipitation (mm/day, MA) | 3.05 | 3.75 | 0.11 | 1.64 | 4.59 |
| Cloud cover (DOS) | 0.50 | 0.36 | 0.13 | 0.51 | 0.86 |
| Precipitation (mm/day, DOS) | 3.02 | 7.09 | 0.00 | 0.01 | 1.90 |
| Hours of night | 6.99 | 1.73 | 5.47 | 5.88 | 8.79 |
| **Fall** | | | | | |
| Cloud cover (MA) | 0.63 | 0.26 | 0.44 | 0.66 | 0.86 |
| Precipitation (mm/day, MA) | 3.54 | 4.83 | 0.11 | 1.57 | 5.09 |
| Cloud cover (DOS) | 0.67 | 0.37 | 0.36 | 0.84 | 1.00 |
| Precipitation (mm/day, DOS) | 4.35 | 8.76 | 0.00 | 0.23 | 4.73 |
| Hours of night | 13.92 | 2.28 | 11.94 | 13.96 | 15.85 |

**Notes:** The table presents summary statistics of the main variables. Sale prices are deflated by the consumer price index (CPI) to 2015 prices, then converted to USD using the January 2, 2023 exchange rate (NOK/USD=9.8413). Size refers to the living area. TOM is the time-on-market, being the number of days between the listing and the sale. *MA* indicates the moving averages of the four days prior to the sale, hence, a one day lagged moving average. *DOS* indicates the day-of-the-sale. Lot size is summarized for non-apartments.

### 3.1 Effect of cloud cover during open houses

Our main regression specification estimates the effect of cloud cover during open houses on sale prices. The regression specification is

$$\begin{aligned}
P_{it} = {} & \alpha + \beta_1 \mathrm{CC}_{jt}^{MA} + \beta_2 \mathrm{CC}_{jt}^{MA} \times \mathrm{Prec}_{jt}^{MA} + \beta_3 \mathrm{CC}_{jt}^{MA} \times \mathrm{HoN}_{jt} \\
& + \beta_4 \mathrm{Prec}_{jt}^{MA} + \beta_5 \mathrm{HoN}_{jt} + \beta_6 \mathrm{Prec}_{jt}^{MA} \times \mathrm{HoN}_{jt} \\
& + \beta_7 \mathrm{PosMaxTemp}_{jt}^{MA} + \beta_8 \mathrm{NegMaxTemp}_{jt}^{MA} + \beta_9 \mathrm{Wind}_{jt}^{MA} \\
& + \mathbf{W}_{jm} \beta_{\mathbf{W}} + \beta_{10} \mathrm{MortgageRate}_t + \mathbf{X}_i \beta_{\mathbf{X}} + \mu_{it} + \mathrm{Zip}_j + \varepsilon_{it},
\end{aligned} \tag{1}$$

where $P_{it}$ is the log of the real sale price for unit $i$ at the sale date $t$. The weather variables $w \in W$ represent the logs of the moving averages of the four days prior to the sale date $t$, denoted with superscript $MA$, in zip code $j$: $\mathrm{CC}_{jt}^{MA}$ is the moving average of average daytime cloud cover, $\mathrm{Prec}_{jt}^{MA}$ is the moving average of precipitation, $\mathrm{PosMaxTemp}_{jt}^{MA}$ is the moving average of maximum temperature (degrees Celsius) if it is positive and else zero, $\mathrm{NegMaxTemp}_{jt}^{MA}$ is the absolute value of the moving average of maximum temperature if it is negative and else zero, and $\mathrm{Wind}_{jt}^{MA}$ is the moving average of instantaneous wind speed forecast in the early afternoon. $\mathrm{HoN}_{jt}$ is the log of the hours of night in the zip code $j$ where unit $i$ is located on sale date $t$.

Because the effect of cloud cover on prospective buyer behavior is likely to vary with the levels of precipitation and hours of night, we include interaction terms (CC $\times$ Prec and CC $\times$ HoN). The first interaction (CC $\times$ Prec) captures the additional impact of precipitation for a given level of cloud cover. This distinction is crucial for isolating the effect of cloud cover (or sunshine) from precipitation, as cloud cover may inadvertently capture precipitation effects, given that precipitation typically occurs alongside cloud cover.[4] The second interaction (CC $\times$ HoN) is important for at least two reasons. First, our sample includes transactions at high latitudes, where daylight hours vary significantly throughout the year. Thus, any cloud cover effect is expected to depend on the brightness or darkness during the relevant period. Second, sunshine exposure may have a more pronounced effect when it is in limited supply. For example, Murray et al. (2010) find that consumer spending on tea decreases during the summer as sunlight increases, holding temperature constant. This finding may be interpreted as an effect driven by longer days,

[4]The correlation between cloud cover and precipitation is 0.44 when measured over the four-day moving average period prior to the sale, and 0.35 when measured on the day of the sale. To assess potential multicollinearity, we re-estimate the model excluding either (i) the interaction between cloud cover and precipitation or (ii) precipitation entirely. Dropping only the interaction term makes the cloud cover coefficient slightly more significant, while dropping precipitation altogether results in somewhat smaller and less significant estimates compared to results in Table 2. This suggests that the inclusion of precipitation, particularly its interaction with cloud cover, helps capture relevant variation without inducing problematic multicollinearity.

given the strong correlation between increased sunlight and extended daylight hours. We further control for the interaction between precipitation and hours of night (Prec $\times$ HoN) as the effect of precipitation may vary with the amount of daylight.[5] As a robustness check, we also estimate a specification of model (1) that includes a three-way interaction between cloud cover, precipitation, and hours of night. This approach provides a more flexible way to capture potential interaction effects among these variables.

Similarly to the specification proposed by Goetzmann et al. (2015), $\mathbf{W}_{jm}$ contains the seasonal weather averages across the years 2013-2023 for every weather variable $w \in W$ and month $m$ for zip code $j$, as described in Section 2. These variables control for seasonality in both cloud cover and other weather variables.[6]

The variable $\text{MortgageRate}_m$ denotes the mortgage rate in the month $m$ when the unit is sold. $\mathbf{X}_i$ is a vector of housing attributes for unit $i$ to control for compositional effects, including log of age (years), log of size (square meters), an indicator taking the value of one if the housing unit is an apartment, the interaction between log of size and the apartment indicator, an indicator taking the value one if the housing unit is not a co-op unit, and an interaction between log of lot size (square meters) and a non-apartment indicator.

Weather exhibits a strong seasonal pattern, while housing prices also follow their own seasonal trends. We expect that controlling for monthly weather conditions will account for price seasonality unrelated to weather. To further address potential confounding factors, we incorporate a series of fixed effects into our model. Specifically, to control for time-invariant unobservables that may correlate with weather—such as institutional differences across municipalities or neighborhoods, including variations in listing and sale timings and the composition of housing units—we include three-digit zip code fixed effects, $\text{Zip}_j$. Additionally, to capture local economic shocks at the municipality level, our most flexible specification incorporates municipality-by-year-by-quarter fixed effects, $\mu_{it}$.

Unobserved heterogeneity among housing units may correlate with weather conditions or hours of night, potentially leading to omitted variable bias. For example, the amount of sunlight entering through living room windows or specific features of a property may make its sale more responsive to certain weather conditions or the timing of its listing and sale within the year. To address concerns regarding omitted variables arising from

[5]Since hours of night vary seasonally by definition, controlling for the interaction between hours of night and precipitation helps account for potential seasonal confounders. The Pearson correlation between the seasonal control for precipitation and the interaction term $Prec$ and $HoN$ is 0.2.

[6]Goetzmann et al. (2015) estimate an alternative model using de-seasoned cloud cover, where the explanatory variable of interest represents the difference between observed cloud cover and its seasonal average, defined as $DCC = log(CC/CC^S)$. We choose not to adopt this approach because it effectively estimates the impact of deviations from the monthly zip code's seasonal average while assuming that these deviations are consistent across all seasons-an assumption that is unlikely to hold in our context.

unobserved heterogeneity, we estimate model (1) using repeat sales with housing unit fixed effects. Furthermore, as a sensitivity analysis, we estimate the model using the repeat sales sample, restricting it to transactions with a holding period of at least 52 weeks. This approach helps mitigate concerns that quick resales may be driven by unobserved factors not captured in the data.

However, it is important to note that using repeat sales, in particular when restricting the holding period, reduces the sample size, potentially introducing attenuation bias due to measurement error. This approach also results in fewer observations for non-apartment transactions, as non-apartments tend to change ownership less frequently than apartments. Nevertheless, omitted variable bias poses a more significant concern than attenuation bias, leading us to favor estimating model (1) with housing unit fixed effects.

## 3.2 Effect of cloud cover on the day of sale

We now extend model (1) to capture the effect of cloud cover on the day of sale on sale prices while also estimating the effect of cloud cover during the open houses. To do so, we add all weather variables measured on the day of the sale to (1). When adding both non-lagged and lagged weather this may raise concerns about introducing multicollinearity, but this is only relevant for highly serially correlated weather variables. In our sample, only maximum temperature may suffer from multicollinearity, still, maximum temperature is treated as a control variable and is not interacted with cloud cover, ultimately mitigating this concern. We estimate the following model:

$$\begin{aligned}
P_{it} = {} & \alpha + \gamma_1 \mathrm{CC}_{jt} + \gamma_2 \mathrm{CC}_{jt} \times \mathrm{Prec}_{jt} + \gamma_3 \mathrm{CC}_{it} \times \mathrm{HoN}_{it} \\
& + \beta_1 \mathrm{CC}_{jt}^{MA} + \beta_2 \mathrm{CC}_{jt}^{MA} \times \mathrm{Prec}_{jt}^{MA} + \beta_3 \mathrm{CC}_{jt}^{MA} \times \mathrm{HoN}_{jt} \\
& + \gamma_1 \mathrm{Prec}_{jt} + \gamma_1 \mathrm{HoN}_{jt} + \gamma_1 \mathrm{Prec}_{jt} \times \mathrm{HoN}_{jt} \\
& + \gamma_1 \mathrm{PosMaxTemp}_{jt} + \gamma_1 \mathrm{NegMaxTemp}_{jt} + \gamma_1 \mathrm{Wind}_{jt} \\
& + \beta_4 \mathrm{Prec}_{jt}^{MA} + \beta_5 \mathrm{HoN}_{jt} + \beta_6 \mathrm{Prec}_{jt}^{MA} \times \mathrm{HoN}_{jt} \\
& + \beta_7 \mathrm{PosMaxTemp}_{jt}^{MA} + \beta_8 \mathrm{NegMaxTemp}_{jt}^{MA} + \beta_9 \mathrm{Wind}_{jt}^{MA} \\
& + \mathbf{W}_{jm} \beta_{\mathbf{W}} + \beta_{10} \mathrm{MortgageRate}_t + \mathbf{X}_i \beta_{\mathbf{X}} + \mu_{it} + \mathrm{Zip}_j + \varepsilon_{it},
\end{aligned} \tag{2}$$

The estimation includes both weather controls for the day of sale and for the four days prior to the sale. We also estimate a specification of model (2) using our repeat sales sample with housing unit fixed effects.

# 4 Results

## 4.1 Effect of cloud cover during open houses

The effects of cloud cover during open houses are summarized in Table 2. Columns (1) through (4) present cross-sectional estimates, with progressively richer sets of fixed effects. Column (3) corresponds to equation (1) and serves as our preferred specification among the cross-sectional models. Columns (5) and (6) report results from the repeat-sales subsample with unit fixed effects; Column (5) represents our overall preferred specification, while Column (6) restricts the sample to transactions with longer holding periods to improve comparability across repeat sales, at the cost of reduced sample size and potentially greater measurement noise. Equation (1) flexibly accounts for seasonality, enabling us to identify seasonal heterogeneity in the effect of cloud cover. To aid interpretation in the presence of interaction terms, we report marginal effects of cloud cover at the means (MEM), both pooled across seasons and within each season.[7] Coefficient estimates are presented in Panel A, while MEMs appear in Panel B. Throughout the paper, our interpretation of the cloud cover effect relies primarily on the MEMs. Because our models are specified in logs, estimates are interpreted as elasticities at the sample means of precipitation and hours of night. For example, a pooled MEM of –0.01 implies that a 1% increase in cloud cover during the open house window (the four days prior to the sale), holding precipitation and night hours constant at their means, is associated with a 0.01% decrease in the sale price.

Column (1) includes municipality-by-year and municipality-by-quarter fixed effects. The marginal effect of cloud cover pooled across seasons (Panel B) is positive but small and statistically insignificant at the 10% level. When disaggregated by season, the effect is negative only in the summer, though still not statistically significant. Column (2) adds three-digit zip code fixed effects to the previous specification. With this finer geographic control, the marginal effects of cloud cover become both larger and statistically significant: the pooled effect and the spring seasonal effect are significant at the 5% level, while the summer effect is significant at the 1% level. All are negative in sign. The fall effect, by contrast, remains small, positive, and statistically insignificant.

Column (3) reports results from our preferred cross-sectional specification, which includes municipality-by-year-by-month and zip code fixed effects. The estimated marginal effect of cloud cover pooled across seasons is similar in magnitude to that in column (2): a 10% (one standard deviation) increase in cloud cover from the mean over the four days preceding the sale is associated with a 0.13% (0.55%) decline in home prices, significant at the 5% level. Seasonal estimates remain consistent, with statistically significant negative

[7] MEMs are calculated using the `lincom` command in Stata 18.

Table 2: Effects of cloud cover on log of home prices

| | Cross-section | | | | Repeat sales | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Panel A: Coefficient estimates | | | | | | |
| Cloud cover | -0.0838 | -0.1217*** | -0.1275*** | -0.1366*** | 0.0170 | 0.0187 |
| | (0.0510) | (0.0374) | (0.0386) | (0.0384) | (0.0513) | (0.0519) |
| Prec. | 0.0118 | 0.0109 | 0.0116 | 0.0120* | 0.0029 | -0.0009 |
| | (0.0098) | (0.0071) | (0.0070) | (0.0071) | (0.0105) | (0.0098) |
| Cloud cover x Prec. | -0.0127 | -0.0059 | -0.0013 | -0.0027 | 0.0063 | 0.0019 |
| | (0.0083) | (0.0063) | (0.0063) | (0.0062) | (0.0091) | (0.0087) |
| Cloud cover x HoN | 0.0433* | 0.0501*** | 0.0516*** | 0.0566*** | -0.0192 | -0.0166 |
| | (0.0227) | (0.0166) | (0.0171) | (0.0170) | (0.0224) | (0.0227) |
| Prec. x HoN | -0.0038 | -0.0032 | -0.0041 | -0.0039 | -0.0010 | 0.0014 |
| | (0.0041) | (0.0029) | (0.0029) | (0.0029) | (0.0043) | (0.0040) |
| Cloud cover (season) | 3.5693*** | 0.6119*** | 0.5543*** | 0.5591*** | 0.0855 | 0.1191 |
| | (0.1907) | (0.0976) | (0.0975) | (0.0971) | (0.1035) | (0.1009) |
| Prec. (season) | -0.4987*** | -0.0800*** | -0.0821*** | -0.0833*** | -0.0221 | -0.0163 |
| | (0.0326) | (0.0152) | (0.0153) | (0.0153) | (0.0157) | (0.0144) |
| Hours of night | 0.2441*** | -0.0100 | -0.0137 | -0.0185 | 0.0170 | 0.0098 |
| | (0.0246) | (0.0150) | (0.0152) | (0.0151) | (0.0161) | (0.0156) |
| Mortage rate | -0.0511*** | -0.0881*** | -0.1039*** | -0.0915** | -0.1136* | -0.1181** |
| | (0.0161) | (0.0120) | (0.0393) | (0.0393) | (0.0622) | (0.0574) |
| N | 52,911 | 52,909 | 52,906 | 52,906 | 12,170 | 11,363 |
| Adj. R. sq. | 0.7772 | 0.8708 | 0.8727 | 0.8733 | 0.9593 | 0.9621 |
| F-stat. (CC and inter.) | 1.9557 | 4.6225*** | 4.4552*** | 4.8112*** | 2.6447** | 1.7206 |
| Fixed effects | MY & MQ | MY & MQ | MYQ | MYQ & MDW | YQ | YQ |
| Zip code FE | | ✓ | ✓ | ✓ | | |
| Unit FE | | | | | ✓ | ✓ |
| Holding time (weeks) | | | | | | ≥52 |
| Panel B: Marginal effects at the means, pooled and by season | | | | | | |
| Pooled | 0.0012 | -0.0148** | -0.0130** | -0.0121* | -0.0201** | -0.0166* |
| | (0.0082) | (0.0065) | (0.0064) | (0.0064) | (0.0089) | (0.0087) |
| Spring | 0.0014 | -0.0158** | -0.0147** | -0.0138** | -0.0206** | -0.0165* |
| | (0.0079) | (0.0062) | (0.0062) | (0.0062) | (0.0087) | (0.0084) |
| Summer | -0.0139 | -0.0316*** | -0.0300*** | -0.0308*** | -0.0133 | -0.0111 |
| | (0.0118) | (0.0088) | (0.0089) | (0.0089) | (0.0122) | (0.0120) |
| Fall | 0.0161 | 0.0034 | 0.0062 | 0.0089 | -0.0268** | -0.0228* |
| | (0.0115) | (0.0089) | (0.0090) | (0.0090) | (0.0120) | (0.0119) |

**Notes:** This table reports results from regressions of the log of sale prices on cloud cover and additional controls. All variables are expressed in natural logarithms and all weather variables are measured as four-day moving averages leading up to the sale. "Season" denotes long-run seasonal averages (2013–2023) for weather variables. Hours of night is abbreviated as HoN. Fixed effects are denoted as follows: M = municipality, Y = year, Q = quarter, and DW = day-of-the-week; thus, MYQ refers to municipality-by-year-by-quarter fixed effects. All regressions include weather controls for maximum temperature and wind speed, as well as their seasonal monthly averages. Additional controls include property age and the mortgage rate. Cross-sectional specifications also include housing attributes: size, an apartment indicator, an interaction between size and apartment status, a non-co-op unit indicator, and an interaction between lot size and a non-apartment indicator. The F-statistic from a joint test of significance for cloud cover and its interactions with precipitation and HoN is reported. Standard errors are one-way clustered at the three-digit zip code-by-year level and reported in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

effects in spring and summer (5% and 1% levels, respectively), and no significant effect in the fall.

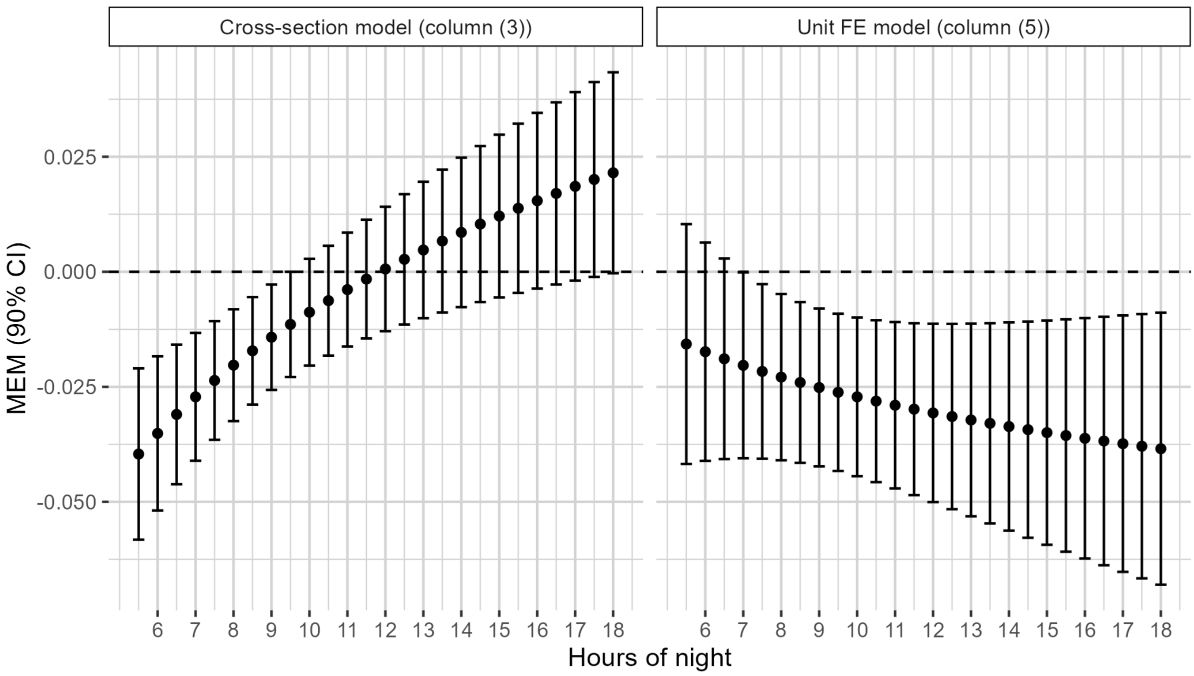
Because open houses are announced well in advance—typically 10 days or more—in the online listings, sellers have limited ability to strategically time them to coincide with favorable weather. Nevertheless, we test for this possibility in column (4). In practice, not every day is equally suitable for scheduling open houses—for example, Saturdays are generally avoided—and the frequency of open houses varies across the week according to local market customs (see Figure A.2). To account for this variation, we include day-of-the-week fixed effects interacted with municipality fixed effects. The estimates in column (4) closely resemble those in column (3), although the pooled cloud cover effect becomes significant at the 10% level. This robustness check suggests that endogenous scheduling with respect to weather is unlikely to drive our main findings.

As discussed in Section 3, the cross-sectional estimates in columns (1) through (4) may be biased by unobserved heterogeneity across housing units—factors potentially correlated with both cloud cover and sale prices. For instance, the value of a balcony likely depends on its orientation and sunlight exposure, and design elements like window size or floor plan can affect how much natural light the interior of a home receives. To address such time-invariant characteristics, we estimate model (1) using unit fixed effects, as shown in columns (5) and (6). Our preferred specification, reported in column (5), relies on the unrestricted repeat sales sample. The estimates imply that a 10% increase in cloud cover from the mean during the four days preceding the sale is associated with a 0.2% decline in home prices, significant at the 5% level. For the median home, this corresponds to a \$704 decrease in price—equivalent to a 1.77% rise in the mortgage rate. A one-standard-deviation increase in cloud cover from the mean corresponds to a 0.85% price drop, or roughly \$2,982 for the median home, equivalent to a 7.50% mortgage rate increase.

Compared to the cross-sectional results in columns (3) and (4), the unit fixed effects estimates in column (5) show a markedly different pattern. The pooled, spring, and fall effects of cloud cover are stronger and statistically significant at the 5% level, while the summer effect is more than halved and no longer significant at conventional levels. Notably, the fall effect becomes negative, with a MEM of –0.0268. There are also substantial shifts in the sign and magnitude of the cloud cover coefficients and its interaction with hours of night (Panel A). Although individual coefficients are not statistically significant, a joint significance test rejects the null that all cloud cover terms are zero (p-value$<$0.05), indicating that the MEMs are primarily driven by the interaction effect between cloud cover and hours of night.

To better understand the cross-sectional and unit fixed effects estimates, we plot the MEMs of cloud cover across different levels of hours of night under no precipitation conditions. As shown in Figure 2, the unit fixed effects estimates from column (5) yield more intuitive patterns than the cross-sectional estimates from column (3). In the cross-sectional models, shorter days are associated with smaller or even positive effects of cloud cover, implying a weaker or even adverse price response to sunshine during darker months—a seemingly counterintuitive result. In contrast, the unit fixed effects model shows that the negative price effect of cloud cover becomes stronger with shorter days, with no positive effects observed. This pattern suggests that sunshine during open houses plays a more important role in buyer valuation when natural light is scarcer. These results underscore how buyers' price perceptions are shaped by the interplay between temporary cloud cover and seasonal daylight availability.

Figure 2: MEMs for different levels of hours of night, preferred models




**Notes**: The figure displays marginal effects at the mean (MEMs) of cloud cover across varying levels of hours of night, holding precipitation fixed at zero. The left panel shows results from the preferred cross-sectional model, and the right panel from the unit fixed effects model, both reported in Table 2. Vertical bars represent 90% confidence intervals.

The divergence between the cross-sectional and unit fixed effects estimates underscores the importance of accounting for time-invariant unobserved heterogeneity across housing units. If such unobserved characteristics were not biasing the cross-sectional results, we would expect the repeat sales estimates to be broadly similar—aside from differences attributable to sample composition or increased standard errors due to the smaller sample size. Instead, the fact that the repeat sales estimates are larger in magnitude and more intuitive suggests that omitting unit-level fixed effects in the cross-section leads to downward bias. While the repeat sales sample contains fewer non-apartment transactions than the full cross-sectional sample, the seasonal distribution of sales is comparable across the two samples. To evaluate whether sample selection might drive the observed differences, we re-estimate the specification from column (3) on the repeat sales sample. This yields smaller coefficients than the full cross-section, consistent with attenuation bias from reduced variation.[8] Together, these findings suggest that selection into repeat sales is unlikely to bias the results in a systematic way. In subsection 4.1.3, we further examine heterogeneity in effects across different types of housing units.

Column (6) restricts the sample to repeat sales of units with a holding period of at least 52 weeks. The estimates are qualitatively similar to those in column (5), though slightly smaller in magnitude and less statistically significant—consistent with attenuation bias due to reduced variation in cloud cover during open houses. Notably, the pooled MEM remains negative but is only significant at the 10% level.

#### 4.1.1 Robustness and sensitivity

To investigate the robustness of our results, we run a battery of tests in Appendix B.1. Specifically, we re-estimate model (1) with alternative controls, including the variable proposed by Kamstra et al. (2003) to account for seasonal affective disorder (SAD) as an alternative to the hours of night; alternative fixed effects; and three-way interaction specifications. The results are overall robust to these alternative choices.

**Seasonal interactions:** We also extend model (1) by interacting cloud cover, and its interactions with precipitation and hours of night, with seasonal dummies, allowing the coefficients on the variables of interest to vary across seasons. The effects of cloud cover become larger in the repeat sales specifications, and are more sensitive in the cross-sectional specifications (see Appendix B.1.2).

**Moving average window and TOM:** We also assess the robustness of our results to alternative specifications of the cloud cover measurement window. Specifically, we vary the length of the moving average from two to six days. We do not extend the window beyond six days, as longer periods would begin to overlap with our seasonal controls. The choice of a four-day window is motivated by both institutional factors and empirical considerations. The results remain broadly consistent across these alternative specifications (see Appendix B.1.3).

Next, we test the sensitivity of our estimates to restrictions on time-on-market (TOM). Shorter TOM increases the likelihood that the open houses fall within the cloud cover

[8] An exception is the fall MEM, which becomes negative but remains statistically insignificant. The positive fall MEMs in columns (1)–(4), which suggest that more sunshine lowers prices, are counterintuitive. Full results are available upon request.

averaging window. In our sample, the maximum TOM is 22 days. We re-estimate our model using subsamples restricted to progressively shorter TOM, down to 10 days. As expected, the estimated cloud cover effect strengthens—up to twice as large in magnitude—as TOM decreases (see Appendix B.1.4). This pattern supports the notion that a shorter TOM increases the precision with which the four-day average captures weather conditions at the time of the open houses.

**Sunshine duration:** In Appendix E, we estimate the effect of sunshine duration, rather than cloud cover, during open houses on home prices. To do so, we use hourly sunshine data from the closest weather station within 20 km, instead of the 18-km grid-level Copernicus data. We re-estimate model (1), replacing the four-day moving average of cloud cover with the corresponding moving average of sunshine duration, measured between 11:00 AM and 6:00 PM CET, i.e., the hours most likely to coincide with open houses.[9] These data are more patchy due to uneven spatial coverage, missing variables across stations, and occasional station downtime. Nonetheless, the results remain consistent with our main findings, albeit somewhat smaller in magnitude, as expected given the lower data quality.

### 4.1.2 Placebo test

To assess whether our results are truly driven by observed cloud cover rather than spurious correlations or confounding factors, we implement a placebo exercise using randomized weather assignments. Specifically, for each transaction in our sample, we randomly draw—with replacement—weather realizations from the full time series of weather data over 2013–2023 (excluding winter months). We use two randomization approaches: (a) drawing the full vector of weather variables simultaneously, and (b) drawing one weather variable at a time, including its corresponding seasonal control. We repeat this procedure 1,000 times, re-estimating the main specification at each iteration. For each run, we record the estimated coefficients and MEMs. We report the mean and standard deviation of these simulated estimates in Tables B.6 and B.7 for the cross-sectional and repeat-sales analyses, respectively.

Results show that the mean MEMs under random weather assignments are close to zero, suggesting that our original findings are unlikely to arise by chance. The only partial exception is when we randomize precipitation, which reveals that the fall MEM is relatively insensitive to this variable, while MEMs in other seasons are more affected. Overall, this placebo exercise supports the validity of our identification strategy.

[9] All other weather variables are likewise averaged over this time window.

### 4.1.3 Heterogeneity by dwelling type and buyer characteristics

We explore whether the effect of cloud cover during open houses varies by dwelling type and buyer characteristics. Table B.7 shows that the price effect is significant for apartments but not for non-apartments. This may reflect greater heterogeneity in non-apartment units, where cloud cover could be correlated with unobserved, time-varying attributes not fully captured by fixed effects.[10] Notably, this pattern also suggests that sunshine-enhanced curb appeal is not the primary mechanism—if it were, we might expect stronger effects for non-apartments, where outdoor features are more common. Instead, the more consistent effects for apartments point toward a cognitive mechanism (see section 5 for more discussion).

Next, we examine heterogeneity across buyer types using administrative data corresponding to the calendar year prior to purchase. We interact the cloud cover variable and its key interactions with indicators for buyer characteristics in our repeat sales specification with unit fixed effects. Figure 3 summarizes the results (full estimates in Table B.8). We find that cloud cover reduces prices primarily for single buyers, especially single adults without children, buyers with a university degree, buyers with above-median wealth or income, women buying alone, and buyers below the sample median age. By contrast, we observe no significant effect for multiple buyers, buyers without higher education, or men buying alone.[11] First-time buyers and non-first-time buyers are similarly affected. These results align with theories suggesting that mood-congruent memory and salience may play a larger role among more sophisticated market participants (e.g., Bodoh-Creed, 2020). However, overlapping confidence intervals across buyer groups prevent us from making strong claims about statistical differences.

## 4.2 Effect of cloud cover on the day of the sale

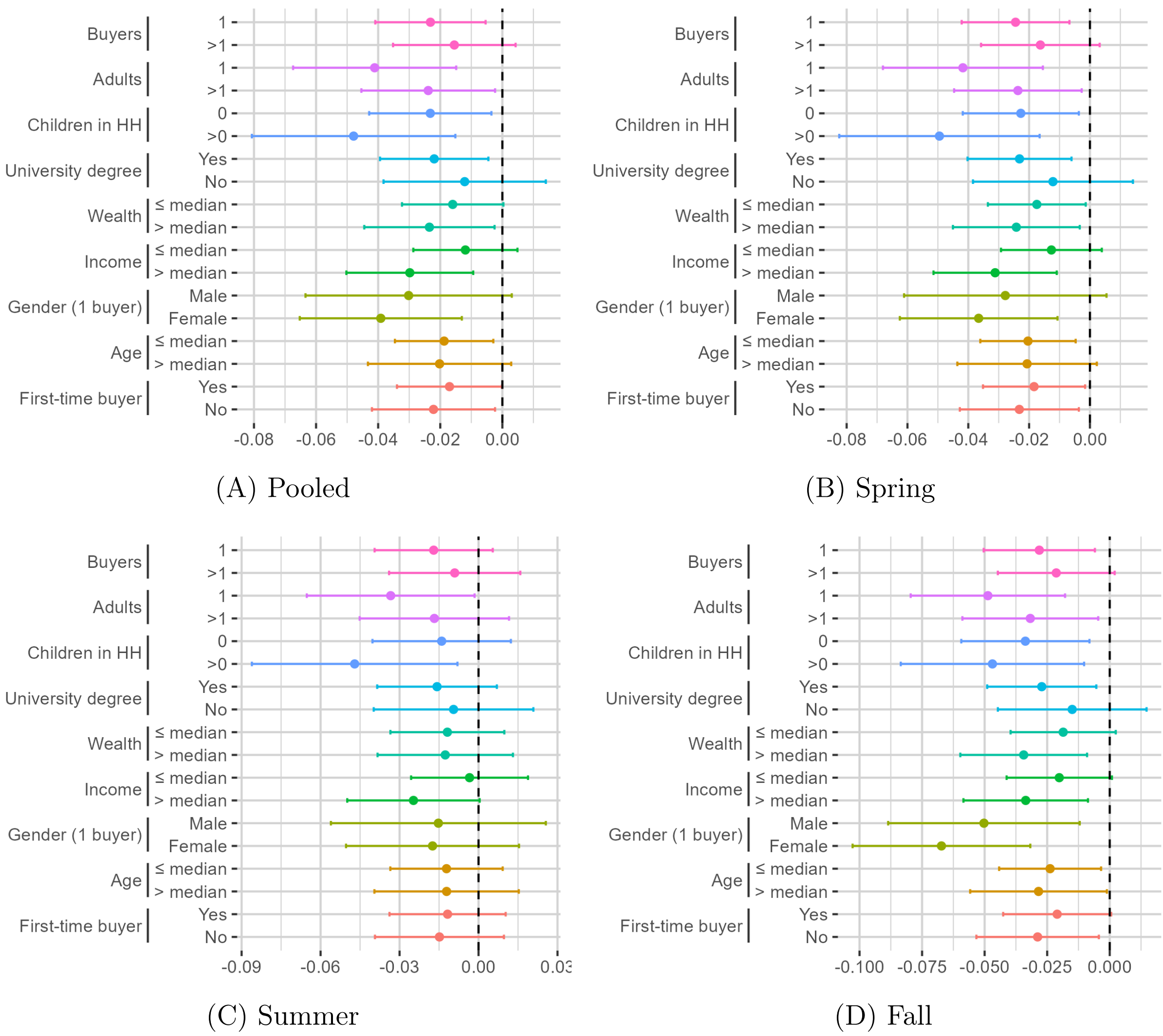
We estimate the marginal effects of cloud cover during open houses (Panel B) and on the day of sale (Panel A) in Table 3. Columns (1) and (2) use the cross-sectional sample, while columns (3)–(5) use the repeat sales sample. First, in columns (1) and (3), we re-estimate model (1), replacing the four-day moving average with cloud cover on the sale date. Second, in columns (2), (4), and (5), we estimate model (2), which includes both the four-day moving average and the day of sale weather variables—allowing us to separately identify the effects of cloud cover on the day of sale and during the open houses.

Across all specifications, cloud cover on the day of sale has no significant effect on home prices and is economically negligible. By contrast, the marginal effects of cloud

[10]The repeat sales sample for non-apartments is relatively small (N $\approx$ 2,000).

[11]Closer inspection shows some evidence that single men are affected when excluding transactions between single men. Results are available upon request.

Figure 3: Buyer heterogeneity - repeat sales




(A) Pooled

(B) Spring

(C) Summer

(D) Fall

**Notes**: The figure shows marginal effects at the means (MEMs) from regressions of log sale price on cloud cover during open houses. Effects are evaluated at sample means and by season, with 90% confidence intervals based on standard errors clustered by three-digit zip code–by–year. For each buyer group, cloud cover and its interactions with precipitation and hours of night are interacted with an indicator for group membership. *Buyers*: number of buyers. *Adults/Children in HH*: number of adults/children (age $\leq$17) in the household, using only transactions where all buyers belong to the same household. *University degree*: at least one buyer holds a degree. *Wealth/Income*: total gross buyer wealth/income (in 2015 NOK, deflated using CPI). *Gender*: buyer gender, for solo buyers only. *Age*: average buyer age. *First-time buyer*: no buyer owns another taxable primary residence.

cover during open houses are consistent with those reported in Table 2, reinforcing our main findings.

Table 3: Marginal effects of cloud cover during open houses and on day of the sale on log of home prices (evaluated at means; MEMs)

| | Cross-section | | Repeat sales | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Panel A: Day of the sale | | | | | |
| Pooled | 0.0018 | 0.0024 | -0.0046 | -0.0035 | -0.0006 |
| | (0.0039) | (0.0040) | (0.0061) | (0.0062) | (0.0062) |
| Spring | -0.0001 | 0.0005 | -0.0040 | -0.0030 | -0.0008 |
| | (0.0035) | (0.0036) | (0.0055) | (0.0056) | (0.0056) |
| Summer | -0.0011 | 0.0002 | -0.0051 | -0.0058 | -0.0033 |
| | (0.0050) | (0.0051) | (0.0076) | (0.0077) | (0.0077) |
| Fall | 0.0070 | 0.0067 | -0.0049 | -0.0015 | 0.0026 |
| | (0.0058) | (0.0058) | (0.0090) | (0.0091) | (0.0090) |
| Panel B: Days prior to the sale, MA(4) | | | | | |
| Pooled | | -0.0127* | | -0.0200** | -0.0174** |
| | | (0.0065) | | (0.0090) | (0.0088) |
| Spring | | -0.0143** | | -0.0201** | -0.0170** |
| | | (0.0063) | | (0.0087) | (0.0085) |
| Summer | | -0.0295*** | | -0.0112 | -0.0112 |
| | | (0.0089) | | (0.0122) | (0.0121) |
| Fall | | 0.0060 | | -0.0294** | -0.0247** |
| | | (0.0091) | | (0.0124) | (0.0121) |
| N | 52,906 | 52,906 | 11,706 | 11,706 | 10,949 |
| Adj. R. sq. | 0.8727 | 0.8727 | 0.9597 | 0.9598 | 0.9623 |
| Fixed effects | MYQ | MYQ | YQ | YQ | YQ |
| Zip code FE | ✓ | ✓ | | | |
| Unit FE | | | ✓ | ✓ | ✓ |
| Holding time (weeks) | | | | | ≥52 |

The table reports marginal effects at the means (MEMs) from regressions of the log of sale prices on cloud cover, based on specification (2). Columns (1)–(2) present cross-sectional estimates, and columns (3)–(5) show results with unit fixed effects. Columns (1) and (3) include only weather conditions on the day of sale, while columns (2), (4), and (5) include both the four-day moving average prior to sale and day-of-the-sale weather. Fixed effects are denoted as follows: MYQ = municipality-by-year-by-quarter, and YQ = year-by-quarter. Standard errors are clustered at the three-digit zip code-by-year level and reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

## 4.3 Effect of cloud cover on buyer participation

Cloud cover during open houses or on the day of the sale may influence buyer interest in attending an open house or in submitting an offer, e.g., by affecting mood or increasing search frictions. For example, inclement weather could deter some prospective buyers from attending open houses, particularly if travel is more difficult or if the home appears less visually appealing under cloudy skies. Alternatively, cloud cover might reduce the attractiveness of outdoor alternatives, lowering the opportunity cost of attending an open house and thus increasing participation.

To test these channels, we examine two outcomes: (1) the number of participants at the open house, and (2) the number of bidders in the online auction, using the supplementary data described in Section 2.[12] Table 4 reports marginal effects at the means from regressing the log of the number of open house participants on cloud cover on the four-day average prior to sale, and the log of the number of bidders on both cloud cover on the day of sale and the four-day average prior to sale. We find no statistically significant effects in either case, suggesting that the pricing response to cloud cover is not explained by changes in buyer participation.

# 5 Mechanisms

This section investigates the behavioral mechanisms that may explain why weather, specifically cloud cover, affects home prices through its timing. A key contribution of our study is to isolate when in the home-buying process such effects emerge. While prior research has shown that weather can influence economic decisions, we provide novel evidence that these effects are concentrated at the initial impression stage, during open house showings, and not at the final decision point, the day of sale. We explore three plausible behavioral channels that can explain this timing pattern: mood-based biases (including mood priming and mood-congruent recall), projection bias, and salience of home attributes. These mechanisms offer distinct predictions about when and how cloud cover, or its counterpart sunshine, may influence buyer evaluations—and help situate our findings within the broader literature on context-dependent preferences and behavioral decision-making.

## 5.1 Mood-induced bias

A potential mechanism is mood misattribution, where buyers subconsciously interpret sunshine-induced good mood as a positive signal about the home itself (Hirshleifer and Shumway, 2003). Our findings align with this mechanism: the price effect appears only during the open house window and is strongest in darker seasons—when sunlight is most scarce and impactful. Two psychological processes support this: (1) mood-priming, in which initial impressions are influenced by an individual's emotional state before or during

[12]The open house participation sample spans October 2021 to November 2023; the bidders sample covers August 2018 to October 2023. Due to the shorter time frames, we do not estimate unit fixed effects.

Table 4: Marginal effects of cloud cover on the number of participants during open houses, and on the number of bidders (evaluated at means; MEMs)

| | Open house participants | | Bidders | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Marginal effects at the means, pooled and by season | | | | | | |
| Pooled | -0.0067 | -0.0326 | -0.0180 | -0.0196 | -0.0579 | -0.0398 |
| | (0.0397) | (0.0408) | (0.0214) | (0.0213) | (0.0414) | (0.0411) |
| Spring | -0.0057 | -0.0296 | -0.0151 | -0.0184 | -0.0561 | -0.0351 |
| | (0.0382) | (0.0391) | (0.0203) | (0.0201) | (0.0397) | (0.0394) |
| Summer | 0.0493 | 0.0036 | -0.0138 | -0.0262 | -0.0319 | -0.0030 |
| | (0.0576) | (0.0591) | (0.0289) | (0.0288) | (0.0481) | (0.0479) |
| Fall | -0.0638 | -0.0734 | -0.0247 | -0.0151 | -0.0821 | -0.0763 |
| | (0.0715) | (0.0713) | (0.0322) | (0.0321) | (0.0608) | (0.0608) |
| N | 7,544 | 7,540 | 17,651 | 17,648 | 17,651 | 17,648 |
| Adj. R. sq. | 0.1202 | 0.1614 | 0.0865 | 0.0922 | 0.0868 | 0.0925 |
| Fixed effects | MYQ(s) | MYQ(s) | MYQ | MYQ | MYQ | MYQ |
| County x DW | | ✓(s) | | ✓ | | ✓ |
| Zip code FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Weather: | | | | | | |
| On open house day(s) | ✓ | ✓ | | | | |
| On sale day | | | ✓ | ✓ | | |
| 4-day average prior to sale | | | | | ✓ | ✓ |

**Notes:** The table reports marginal effects at the means from regressions of the log number of open house participants on cloud cover on the exact days of the open house(s) (columns 1-2), and the log number of bidders on cloud cover on the sale day (columns 3-4) and over the four days prior to sale (columns 5-6). For the open house participation analysis, the sample spans October 2021 to November 2023, with each observation corresponding to a unique open house date–transaction pair. If multiple open houses occur on the same day, their participant counts are summed. The bidders analysis uses data from August 2018 to October 2023. Fixed effects are denoted as follows: MYQ = municipality-by-year-by-quarter, and DW = day-of-week. Fixed effects for the open house analysis are indexed to open house dates (denoted with "(s)"). All regressions include controls for maximum temperature, wind speed, and their seasonal monthly averages, as well as unit characteristics: age, mortgage rate, size, an indicator for whether the unit is an apartment, the interaction between size and the apartment indicator, an indicator for non-co-op ownership, and the interaction between lot size and a non-apartment indicator. Standard errors are one-way clustered at the three-digit zip code-by-year level and are reported in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

the open house (e.g., Schwarz and Clore, 1983; Johnson and Tversky, 1983), and (2) mood-congruent recall, where buyers are more likely to retrieve positive impressions when experiencing a similar emotional state later on (Bower, 1981; Forgas, 2017).

To test the latter, we estimate whether consistent cloud cover between open houses and sale day amplifies the cloud cover effect. Results (Table C.1) show that price effects are strongest when cloud cover is most similar across both periods, consistent with mood-congruent recall. We also test whether broader exposure to low sunlight prior to the open houses influences prices, in the spirit of seasonal affective disorder effects documented in financial markets (e.g., Kamstra et al., 2003). Table C.2 indicates that cloud cover in the days leading up to the open houses has a limited effect on home prices. The only notable finding is a small, statistically weak negative effect on the pooled MEM for the 4-day window prior to the open houses, significant at the 10% level. An exception arises in the fall, where cloud cover 4–10 days before the open houses appears to influence prices, suggesting a mood-priming mechanism associated with seasonal darkness during that period.

## 5.2 Projection bias

Projection bias, where current states distort expectations of future utility, may also play a role (Loewenstein et al., 2003). Conlin et al. (2007) show that weather affects catalog returns, while Busse et al. (2015) find convertible cars purchased on sunny days are sold sooner, suggesting regret or misjudged long-term utility. We adopt the approach in Busse et al. (2015) by testing whether homes bought under sunny conditions are resold earlier. We find no such pattern (Table C.3). The null result may not be surprising: unlike cars, homes are high-stakes, long-horizon purchases with high transaction costs and cannot easily be "returned."

## 5.3 Salience

Bordalo et al. (2013) present a model of context-dependent consumer choice in which decision weights are distorted toward attributes that are visually or contextually salient. In their framework, salience increases when an attribute deviates from a reference point, either in absolute terms or relative to the choice environment. Applied to housing, salience may operate along two distinct but complementary dimensions. First, *reference-dependent salience* implies that features such as cloud cover or sunshine may draw more attention when they differ sharply from recent weather conditions, influencing perceptions through contrast. Second, *attribute-dependent salience* captures the idea that some home characteristics, such as natural light or exterior views, may be more visually responsive to weather variation and therefore receive greater cognitive weight. For example, a sunny open house may make large windows feel especially inviting, while a gloomy day may suppress the appeal of such features or even create disappointment if buyer expectations are unmet. These two salience channels may interact: a weather anomaly may be particularly influential when it alters the perception of attributes that are themselves sensitive to light or visibility.

To test whether our findings are consistent with reference-dependent salience, we estimate model (1) with unit fixed effects, interacting the moving average of cloud cover during the open houses (and its interactions with precipitation and hours of night) with an indicator for whether conditions at the open houses were cloudier or less cloudy than during the prior $x \in \{4, 6, 8, 10\}$-days. The results (Table C.4) provide support for reference-dependent salience.[13] When open houses occur under cloudier conditions than in the preceding 4–8 days (i.e., unexpectedly gloomy), the marginal effect of cloud cover becomes more negative and statistically significant. By contrast, when conditions are less gloomy than in the prior period, the effects are smaller and not significant.[14]

Next, we investigate whether our findings are consistent with attribute-dependent salience. First, Table B.7 shows that cloud cover has a larger negative effect on prices for apartments than for non-apartments. This is consistent with apartments being more reliant on interior lighting and views—features more sensitive to weather-induced visual changes. Lacking outdoor features, apartment appeal depends more heavily on how the interior is experienced, making them more vulnerable to salience distortions. Second, in Table C.5, we examine whether the cloud cover effect varies with housing vintage. In Panel A (all homes), excluding older units strengthens the negative marginal effect of cloud cover, consistent with newer homes having architectural features (e.g., large windows, open layouts) that are more responsive to light.[15] Replicating the same test only for apartments in Panel B, we observe an even larger effect of cloud cover when limiting the sample to newer units.[16] This pattern reinforces the idea that when buyers rely more on interior features—such as lighting and views—for valuation, those features become more susceptible to weather-induced salience effects.

Together, these findings suggest that salience may operate along both reference- and attribute-dependent dimensions. Reference-dependent salience determines when attention is drawn (e.g., unexpectedly bad weather), while attribute-dependent salience shapes what buyers focus on (e.g., homes with more sunlight exposure). The interaction between these

[13] For longer reference windows ($x = 10$ days), the pattern becomes noisier, possibly because cloud cover further back in time may be less salient in the buyer's mental comparison set. Narrower windows (4–8 days) more plausibly reflect weather that buyers recall when forming expectations at the time of the open houses. Moreover, because the estimates in Panel A (less cloud cover during open houses than prior) and Panel B (more cloud cover during open houses than prior) are similar in magnitude for $x = 10$, the model may be picking up residual seasonality or other time-varying factors not directly related to changes in cloud cover.

[14] This test may also partly reflect mood priming, as weather leading up to the open house might influence buyers' baseline emotional state. However, the asymmetry, where gloomier-than-usual conditions yield larger negative effects while less gloomy conditions do not, is more consistent with salience. Mood-based mechanisms typically predict more symmetric effects of weather deviations. Salience theory, particularly when coupled with negativity bias, suggests that negative surprises (e.g., overcast conditions) are more likely to distort buyer attention and valuation.

[15] Older homes typically have smaller and/or fewer windows, whereas newer homes tend to feature larger and/or more windows. This may be due to advancements in heat loss reduction technology, as well as a greater emphasis in modern architecture on maximizing natural light.

[16] The attenuation of the cloud cover effect for homes built in or after 1980 may reflect variation in architectural styles during that period, which may have made natural light less responsive to external weather conditions, thereby reducing the salience of cloud cover during showings.

two mechanisms helps explain why transient cues like cloud cover may affect valuations, and why some homes are more susceptible than others.

### 5.4 Discussion of mechanisms

Our findings are most consistent with two mechanisms triggered by cloud cover: mood-based effects, operating through mood priming and mood-congruent recall, and salience-based effects, encompassing both reference-dependent and attribute-dependent salience. In contrast, we find little evidence for projection bias. These results contrast with Busse et al. (2015), where projection bias in car purchases is plausible due to relatively low transaction costs. Our findings also differ from Conlin et al. (2007), whose product context (winter gear) is more conducive to return behavior.

Importantly, the cloud cover effects we detect are specific to the open house period, rather than the sale day. This aligns with a psychological interpretation: the moment when buyers form their impressions matters most, not the day the transaction is finalized. In short, cloud cover shapes how buyers perceive housing attributes—either by influencing their mood or due to salience. These effects are transient and context-specific, yet they systematically influence a high-stakes financial decision: the price of a home.

## 6 Conclusions

This paper contributes to a growing literature on context-dependent decision-making by identifying when behavioral biases—specifically those induced by weather—affect economic outcomes. While previous studies have documented effects of weather on financial markets and durable goods purchases, little is known about *when* during the decision process such biases influence high-stakes consumer behavior. Using granular data from the Norwegian housing market, we examine the role of cloud cover in shaping home prices and isolate the timing of its impact across different stages of the sales process.

Despite the large financial stakes and high deliberation typically involved in housing decisions, we find that buyers are affected by incidental weather conditions: a one standard deviation increase in cloud cover during open houses reduces sale prices by 0.85% (p-value $< 0.05$), equivalent to nearly \$3,000 for the median-priced home, or a 7.5% increase in the mortgage rate. These effects are robust across specifications and concentrated during the first in-person impression stage—namely, the open house period. In contrast, we find no effect of cloud cover on buyer turnout at open houses, bidding behavior during auctions, or price formation at the final decision point (the day of sale).

We explore several behavioral mechanisms to explain this pattern. Our evidence is consistent with mood-based channels and with a salience mechanism, in which sunshine alters how buyers perceive and weigh home attributes during open houses. The absence of resale behavior consistent with buyer's remorse, and lack of evidence for projection bias, further supports these interpretations.

Our findings suggest that even in markets with high financial stakes and deliberate decision-making, incidental environmental factors such as cloud cover can bias valuations. This has implications not only for household wealth and borrowing decisions but also for how behavioral factors shape asset pricing in contexts where buyers interact directly with the good being purchased. More generally, our approach illustrates how identifying the timing of behavioral influence can help unpack the psychological drivers behind economic choices.

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# Online Supporting Material

**For "Cloudy Judgments: The Timing of Weather-Induced Biases"**

by Andreas E. Eriksen and Cloé Garnache

## A Additional data background

This section presents further information on the dataset underlying our analysis, covering the data preparation steps and summary statistics.

### A.1 Housing sales transactions

Our primary transaction dataset from Eiendomsverdi AS is cleaned through a series of steps. First, we exclude transactions with time-on-market (TOM) exceeding twice the median (i.e., longer than 22 days). We then trim the 1st and 99th percentiles of asking and selling prices within each municipality-year group, and winsorize living area size at the same percentiles. The sample is further restricted to transactions occurring in spring, summer, and fall, and to municipalities in southeastern Norway: Asker, Bærum, Drammen, Fredrikstad, Kristiansand, Lillestrøm, Moss, Nordre Follo, Oslo, Sandefjord, Sarpsborg, Skien, and Tønsberg. According to Statistics Norway, these municipalities accounted for approximately 30 percent of the national population in 2021—about 1.65 million out of 5.4 million residents (Statistics Norway, 2024). A detailed overview of the data cleaning process is provided in Table A.1.

Table A.1: Cleaning steps, main data

| Cleaning step | # of transactions |
|---|---:|
| Initial | 160,541 |
| Keep relevant areas | 133,749 |
| Keep sales with TOM of at most 2 times the median (22 days) | 97,666 |
| Keep sales with TOM of at least 7 days | 84,974 |
| Trimming | 82,800 |
| Drop the winter | 68,926 |
| Keep housing units in southeastern municipalities | 55,823 |

**Notes:** The table shows the steps taken for cleaning the main data set and how many transactions remain after each step.

To examine whether certain buyer groups are more susceptible to the influence of cloud cover, we merge these data with buyer characteristics. These are measured at the end of the calendar year preceding each transaction, to reflect buyers' status at the time of purchase. Because buyer data are only available through 2019, transactions in 2021 are matched with characteristics from the end of 2019. Summary statistics for the buyer sample are presented in Table A.2.

Table A.2: Summary statistics - buyers

| | Mean | SD | 25th pct. | Median | 75th pct. |
|---|---|---|---|---|---|
| **Panel A:** All sales (N = 55,823) | | | | | |
| # of buyers | 1.51 | 0.52 | 1.00 | 2.00 | 2.00 |
| All buyers from same HH | 0.84 | | | | |
| Adults in HH | 1.88 | 0.84 | 1.00 | 2.00 | 2.00 |
| Any children in HH | 0.32 | | | | |
| Any buyers with university degree | 0.29 | | | | |
| Gross wealth (in 1,000 USD) | 225.89 | 3,554.52 | 40.99 | 99.51 | 195.81 |
| Gross income (in 1,000 USD) | 82.27 | 116.77 | 43.09 | 66.79 | 103.85 |
| Share of women | 0.52 | 0.36 | 0.50 | 0.50 | 1.00 |
| Age | 37.53 | 13.63 | 27.00 | 33.00 | 45.00 |
| First-time buyers | 0.40 | | | | |
| **Panel B:** Final sales of repeat sales sequences (N = 7,160) | | | | | |
| # of buyers | 1.45 | 0.52 | 1.00 | 1.00 | 2.00 |
| All buyers from same HH | 0.82 | | | | |
| Adults in HH | 1.84 | 0.87 | 1.00 | 2.00 | 2.00 |
| Any children in HH | 0.24 | | | | |
| Any buyers with university degree | 0.29 | | | | |
| Gross wealth (in 1,000 USD) | 202.85 | 2,369.01 | 30.97 | 83.63 | 165.24 |
| Gross income (in 1,000 USD) | 72.41 | 70.80 | 38.58 | 58.02 | 92.34 |
| Share of women | 0.54 | 0.38 | 0.00 | 0.50 | 1.00 |
| Age | 35.91 | 13.32 | 26.00 | 31.00 | 43.00 |
| First-time buyers | 0.48 | | | | |

**Notes:** This table reports summary statistics for buyer characteristics. Panel A shows statistics for the full sample, while Panel B focuses on the repeat sales sample, using buyer characteristics from the final transaction in each repeat sales sequence. Variables are listed in the order they appear in Figure 3. "# of buyers" refers to the number of buyers involved in the transaction. "All buyers from same HH" is an indicator equal to one if all buyers belong to the same household. "Adults in HH" denotes the minimum number of adults (age$\geq$18) across the buyers' households. "Any children in HH" is equal to one if any buyer's household includes children (age$\leq$17). "Any buyers with university degree" indicates whether at least one buyer holds a university degree. "Gross wealth" and "gross income" are the combined total gross wealth and income of all buyers, deflated to 2015 prices using the consumer price index and converted to USD using the January 2, 2023 exchange rate (NOK/USD = 9.8413). "Share of women" denotes the proportion of female buyers; a value of 0 indicates all-male buyers, and 1 indicates all-female buyers. "Age" is the average age of the buyers. "First-time buyers" is an indicator equal to one if none of the buyers owned a primary residence, based on taxable property records.

## A.2 Supplementary data with open house dates and participation, and bidding information

The supplementary dataset contains richer housing sales transactions data but is smaller than our main dataset. In particular, it contains the exact dates of open houses, the number of participants at open houses, and the number of individuals submitting bids. The dataset comes from the realtor firm, DNB Eiendom—the second largest realtor firm in Norway with about 20 percent market share.

To match the DNB data as best as possible to our main dataset, we retain units sold in municipalities south of latitude 61.5, excluding those in the former counties of Hordaland, Rogaland, and Vest-Agder—except for Kristiansand and Vennesla. Kristiansand, already part of our main sample, lies in the southwest of the target region. Due to limited sample size, we include rural areas; however, this comes at the cost of greater unobserved heterogeneity. Notably, the dataset does not distinguish buyer types (e.g., individuals, firms, or institutions), further complicating interpretation. As a result, we do not replicate our main price effect estimates using these data. The final sample covers 104 municipalities. While it includes all municipalities in southeastern Norway, the dataset from DNB Eiendom contains considerably fewer observations than our main Eiendomsverdi sample. Data cleaning is conducted at the county level and summarized in Table A.3.

**Open house dates and choice of a four-day moving average:** Because this supplementary dataset contains the exact dates of open houses, we use it to validate our choice of a four-day moving average to measure cloud cover during the open houses (see also Subsection 2.2). Figure A.1 illustrates the distribution of days between the first open house and sale in the full sample and when restricting to transactions with at least two open houses, and figures A.2-A.3 illustrate the distribution of days between the last open house and sale and between the first and last open houses in four municipalities in our sample. Among transactions with only one day of open houses, 78% result in a sale the following day, and 91% within four days. When open houses span multiple days, 73% of units are sold within four days of the first open house. Beyond this window, the time to sale increases rapidly, often due to failed auctions and subsequent new rounds of open houses. We assume that buyers who remain interested in the unit would attend the latest round of open houses, making these most relevant for their decision-making.

We use an unweighted four-day average of cloud cover, as open houses may occur on any of those days. Weighting based on open house distribution would overemphasize the day immediately preceding the sale, yet sunshine should matter only during the open houses themselves, not based on temporal proximity to the sale date. Weighting could therefore introduce unnecessary noise. An alternative would be to include separate lags for each day's cloud cover, but this would complicate interpretation without yielding

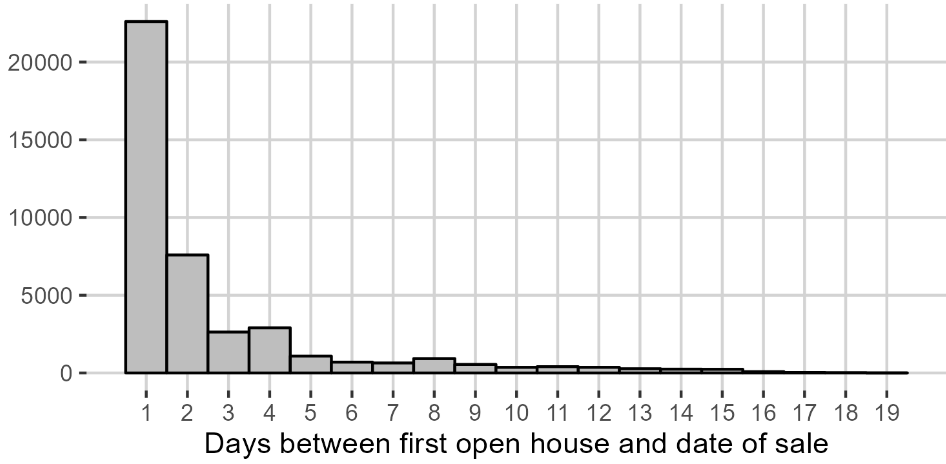
Table A.3: Cleaning steps, supplementary data

| Cleaning step | # of transactions |
|---|---|
| Initial | 95,387 |
| Keep on-market sales | 94,923 |
| Keep second-hand market realtor offices | 94,655 |
| Drop duplicates | 94,655 |
| Drop sales with more than one accepted bid | 93,679 |
| Keep sales between 2018 and 2023 | 92,115 |
| Drop bids with missing timestamp for bids | 92,084 |
| Drop sales without sales date | 90,801 |
| Keep municipalities below latitude 61.5 | 79,044 |
| Keep auctions lasting at most 7 days (received first bid to sale) | 66,916 |
| Keep sales with open houses after the listing (dropping previously withdrawn units) | 52,988 |
| Keep sales with TOM of at most 22 days (same as used on the main sample) | 43,932 |
| Drop units with first (and last) open house after the sale | 42,789 |
| Drop sales with missing size | 42,761 |
| Drop sales assigned to the wrong county | 42,748 |
| Trimming | 41,646 |
| Drop the winter | 35,077 |
| Keep southeastern municipalities | 29,372 |
| Keep transactions with participation at precise open house dates | 12,170 |

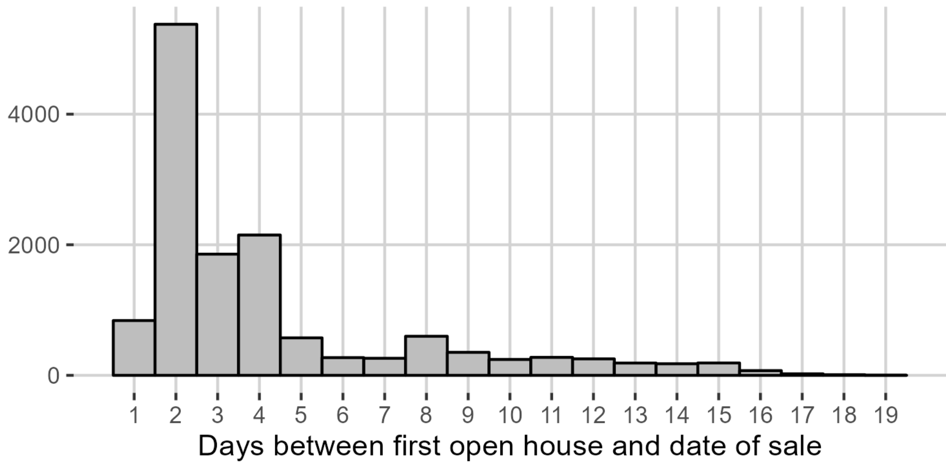
**Notes:** This table outlines the data cleaning steps applied to the dataset containing open house dates, showing how many transactions remain after each step. The final sample is used for the open house participation regressions in Table 4, while the bidder regressions use the sample from the second-to-last step. The raw dataset is initially at the bid level, and additional filters are applied to retain only well-behaved sales, excluding records with typos or clerical errors. Trimming procedures follow those used for the main dataset but are conducted at the county level rather than the municipality level.

clearer identification, given the presumed equal relevance of sunshine across the open house window.

Figure A.1: Distributions of the days between first open house and sale



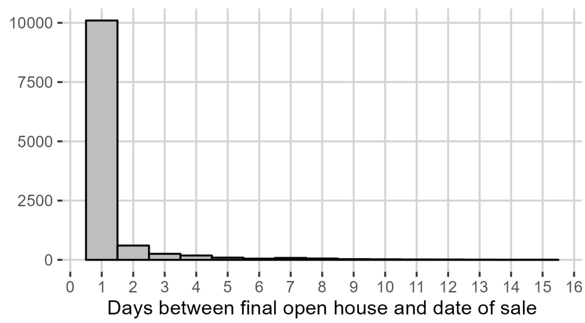

(A) Full sample



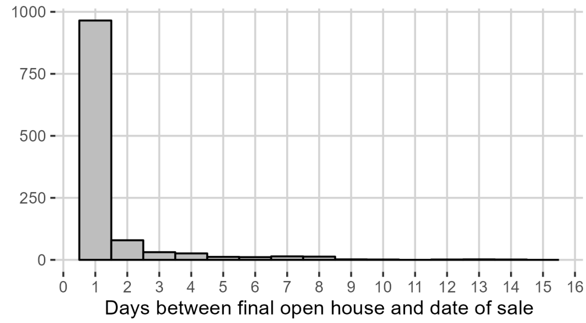

(B) At least two open houses

**Notes**: The figures show distributions of the number of days between the first open house and the date of sale. Panel (B) restricts the sample to transactions with at least two open houses, which may occur on the same or on different days.

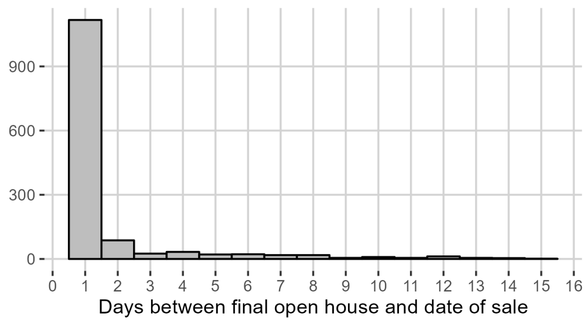
Figure A.2: Distributions of the days between last open house and sale



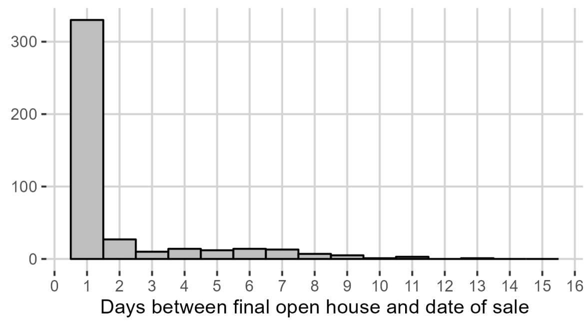

(A) Oslo




(B) Lillestrøm



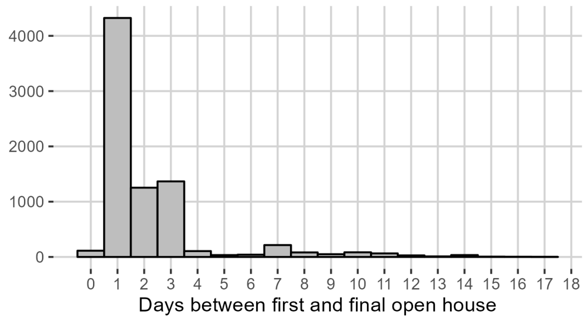

(C) Drammen



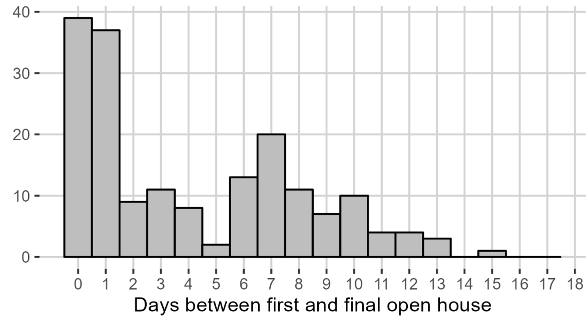

(D) Skien

**Notes**: The figures show distributions of the number of days between the last open house and the date of sale across four different municipalities. We chose these four municipalities to display how these distributions differ.

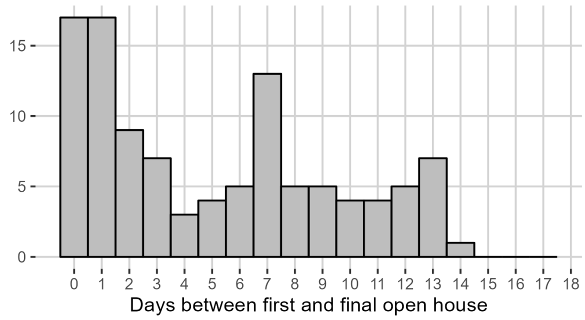
Figure A.3: Distributions of the days between first and last open houses



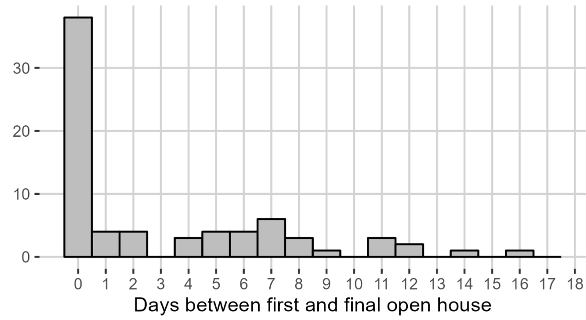

(A) Oslo




(B) Lillestrøm



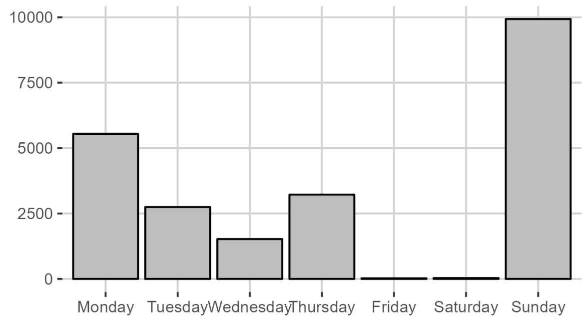

(C) Drammen



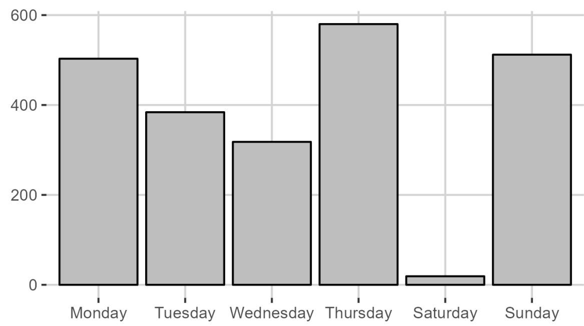

(D) Skien

**Notes**: The figures show distributions of the number of days between the first and the last open houses for a subsample comprising sales with exactly two open houses across four different municipalities. We chose these four municipalities to display how these distributions differ.

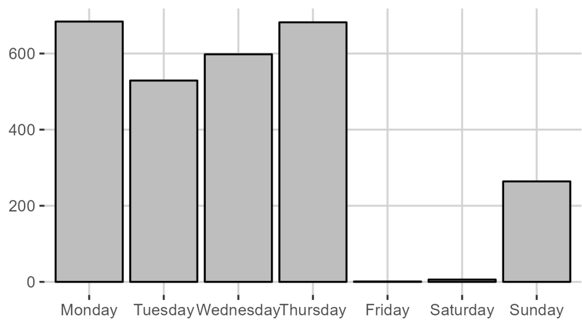
Figure A.4: Distribution of the days of the week during which open houses are conducted



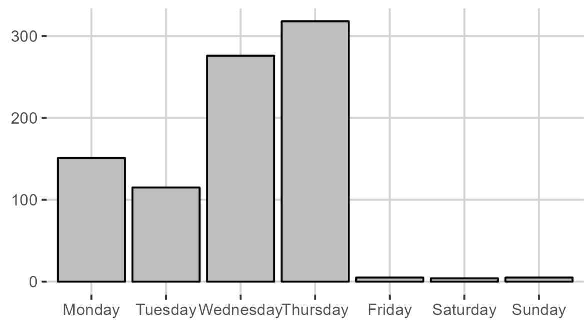

(A) Oslo




(B) Lillestrøm




(C) Drammen




(D) Skien

**Notes**: The figures show which days-in-the-week open houses are conducted across four different municipalities. These are based on the first and last open house dates. If there are more open houses these are not included. In our supplementary sample, more than 98 percent of sales have either one or two open houses. We chose these four municipalities to display how these distributions differ.

## A.3 Weather data

The weather data from the Copernicus Climate Change Service are collected for the period 2013-2023.

*Cloud cover:* We use cloud cover measured as a daily daytime average. Cloud cover is calculated by classifying pixels in a high-resolution grid as cloudy or not, then the number of pixels classified as cloudy is compared to the total number of pixels in a larger grid cell to find the fractional cloud cover.[17] Daytime averages are not available in darker periods, starting in mid October and ending in February. Observations are determined as daytime observations based on when the satellite crosses the equator during illuminated conditions and the direction of the satellite's trajectory. When the daytime cloud cover average is not available for a particular day, we use the daily cloud cover average. The cloud cover median grid cell size is 336 square kilometers with rectangular grid cells. Cloud cover is provided on a scale from 0 to 100, in which 0 is clear sky and 100 is fully cloud covered sky. We scale this to being between 0 and 1.

*Precipitation and maximum temperature:* The consolidated data with precipitation and maximum temperatures are provided on a one-by-one kilometer resolution. Precipitation is provided in millimeters per day and is accumulated from 6:00 AM UTC the reported date to 6:00 AM UTC the day after. The maximum temperature is provided in Kelvin which we convert to Celsius by subtracting 273.15. It is the maximum in the time interval between 6:00 PM UTC the date before and 6:00 PM UTC the date of the reported observation. Most likely the temperature we use is the one falling on the day of the reported observation.

*Wind speed:* Wind speed is a short forecast based on the ERA5 model, and we find that the median grid cell size is approximately 100 square kilometers with rectangular grid cells. Wind speed is found from the (10m) u- and v-components of wind using the Pythagorean Theorem: $\mathrm{WS} = \sqrt{u^2 + v^2}$. The forecasts we use are made for 12:00 PM UTC, and it is meant as a control variable because the local wind speed is highly dependent on local factors such as topology and building structure. Note that Norway is located in the CET timezone and uses daylight saving times, so that during winter time the wind speed is for 1:00 PM and during summer time it is for 2:00 PM.

*Aggregation to the zip code level:* The weather data are converted from grids to zip codes, taking the average of the grid values if more than one grid is overlapping the zip codes. Distributions of the four weather variables are provided in Table A.4 and Figure A.5.

[17] Details on the classification algorithm is provided by Dybbroe et al. (2005). For more information about the data, see the Copernicus Climate Change Service Data Store webpage at https://cds.climate.copernicus.eu/datasets/satellite-cloud-properties?tab=overview.

*Hours of night:* We calculate hours of night (hereafter HoN) using the the method proposed by Kamstra et al. (2003) to calculate their SAD variable, although we do not truncate the hours of night to zero in the spring and summer as they do for SAD, and do not subtract 12.

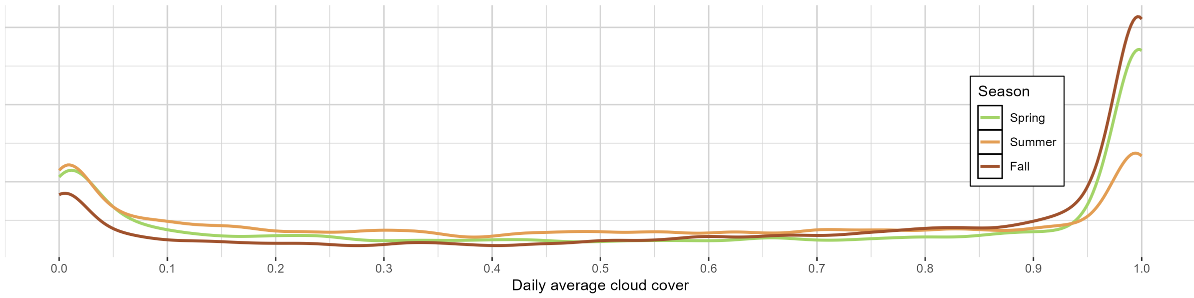
*Log transformation of weather variables:* All weather variables are log transformed plus one due to the presence of zeros. The maximum temperatures are provided in Celsius, therefore, we take the natural logarithm of the absolute value of these plus one, then create two temperature variables: one for positive temperatures and one for negative temperatures.

Table A.4: Weather distributions, 2013-2023, by season

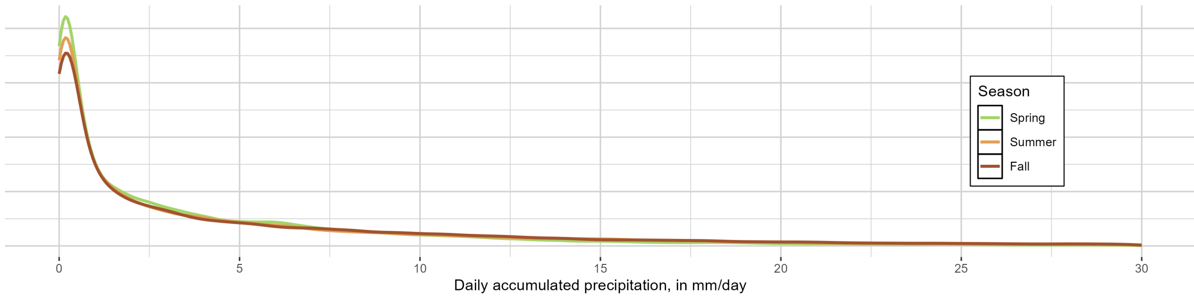
| | 10 pct. | 20 pct. | 30 pct. | 40 pct. | 50 pct. | 60 pct. | 70 pct. | 80 pct. | 90 pct. |
|---|---|---|---|---|---|---|---|---|---|
| **Spring** | | | | | | | | | |
| Cloud cover | 0.02 | 0.10 | 0.26 | 0.47 | 0.68 | 0.86 | 0.98 | 1.00 | 1.00 |
| Precipitation | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.10 | 0.60 | 2.54 | 6.77 |
| Max temp. | 3.52 | 6.05 | 7.76 | 9.33 | 10.84 | 12.32 | 14.13 | 16.58 | 19.69 |
| Wind speed | 1.11 | 1.54 | 1.94 | 2.28 | 2.64 | 3.00 | 3.39 | 3.90 | 4.67 |
| **Summer** | | | | | | | | | |
| Cloud cover | 0.01 | 0.10 | 0.22 | 0.36 | 0.52 | 0.66 | 0.80 | 0.93 | 1.00 |
| Precipitation | 0.00 | 0.00 | 0.00 | 0.00 | 0.07 | 0.39 | 1.61 | 4.38 | 10.18 |
| Max temp. | 17.48 | 18.76 | 19.71 | 20.54 | 21.36 | 22.23 | 23.21 | 24.56 | 26.70 |
| Wind speed | 1.01 | 1.46 | 1.82 | 2.16 | 2.51 | 2.86 | 3.25 | 3.73 | 4.55 |
| **Fall** | | | | | | | | | |
| Cloud cover | 0.03 | 0.23 | 0.49 | 0.68 | 0.83 | 0.94 | 0.99 | 1.00 | 1.00 |
| Precipitation | 0.00 | 0.00 | 0.00 | 0.01 | 0.20 | 0.89 | 2.63 | 5.99 | 12.48 |
| Max temp. | 2.99 | 5.92 | 7.94 | 9.77 | 11.44 | 13.04 | 14.49 | 16.19 | 18.53 |
| Wind speed | 0.96 | 1.38 | 1.76 | 2.14 | 2.50 | 2.89 | 3.31 | 3.88 | 4.83 |

**Notes:** The table shows the weather distributions in our 13 municipalities in the period 2013-2023. All weather variables are extracted from gridded map data to zip codes. Cloud cover is a share between 0 (clear sky) and 1 (fully clouded), precipitation is in millimeters, max temperature is in Celsius, and wind speed is in meters per second.

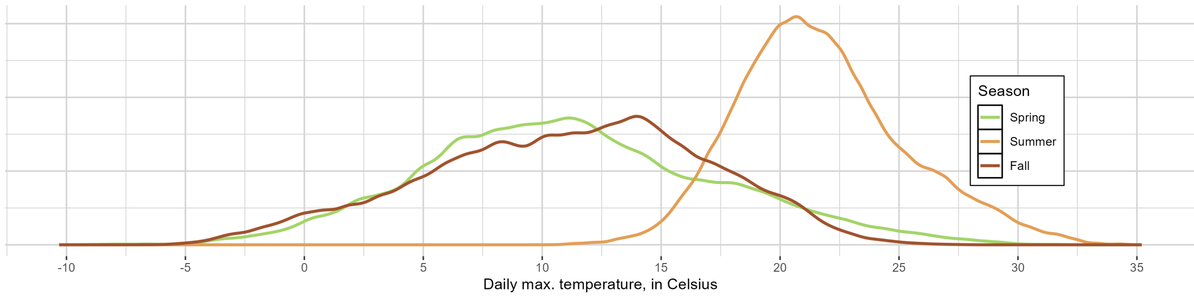
Figure A.5: Observed weather distributions in south-east Norway, 2015-2023



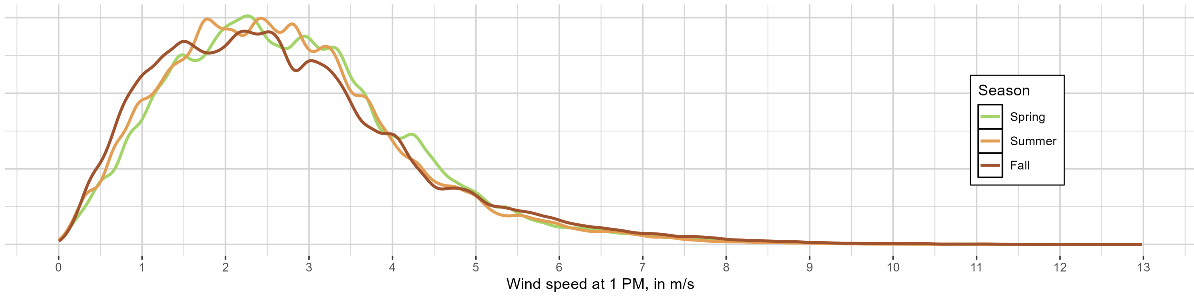

(A) Daily average cloud cover, from 0 (clear sky) to 1 (fully covered)




(B) Daily accumulated precipitation, in millimeters




(C) Daily maximum temperature, in Celsius




(D) Wind speed at 1:00 PM, in meters per second

**Notes**: The figure presents distributions of the weather variables using Gaussian kernels. Precipitation in panel (B) is zoomed in at (0,30) and does not include the boundaries.

# B Additional results

## B.1 Effect of cloud cover during open houses on home prices - Robustness and sensitivity

### B.1.1 Fixed effects and three-way interactions

We test the sensitivity of our results to changes in the main specification, as shown in Table B.1. For the cross-sectional model, we begin by including only cloud cover, precipitation, their seasonal controls, hours of night, and fixed effects—excluding interactions and other controls (column 1). The pooled marginal effect magnitude (MEM) remains similar at –0.0126 but is no longer statistically significant. When we add the remaining controls (e.g., size, apartment type), while still excluding interactions, the MEM is virtually unchanged at –0.0127 and becomes statistically significant (column 2). Since interactions are excluded in both models, seasonal effects cannot be separately identified.

Next, we exclude the controls but retain the interaction terms (column 3). This results in smaller and statistically insignificant MEMs, including by season. This pattern suggests that compositional controls play an important role in reducing residual variance and improving precision. We also estimate a model including a three-way interaction between cloud cover, precipitation, and hours of night (column 4). The results are nearly identical to our main specification.

Finally, we follow the approach in Kamstra et al. (2003) and truncate the (log of) hours of night to zero for all seasons except fall, capturing potential seasonal affective disorder (SAD) effects (column 5). This adjustment yields a stronger MEM for spring (–0.0202, significant at the 1% level) and summer (–0.0195, significant at the 5% level), while the fall effect remains insignificant and the pooled effect is unchanged.

We repeat the sensitivity analysis for the repeat sales specification, first by adding the three-way interaction between cloud cover, precipitation, and hours of night, and second by truncating the hours of night variable.[18] In the first case, the results are largely consistent with our main estimates, except for a stronger fall effect: the MEM increases to –0.0347 and is significant at the 1% level (column 7). This suggests that allowing for additional flexibility in how precipitation interacts with cloud cover amplifies the estimated effect in fall.

In the second case, we truncate the hours of night to zero for all seasons except fall (column 8). The pooled MEM is slightly lower at –0.0177 (significant at the 5% level), while seasonal effects remain similar in magnitude but lose statistical significance. We

[18] We also estimate the repeat sales specification while adding day-of-the-week fixed effects. The results are nearly identical to our main repeat sales specification. Results are available upon request.

Table B.1: Sensitivity to alternative controls, fixed effects, and three-way interactions

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Marginal effects at the means, pooled and by season | | | | | | | | |
| Pooled | -0.0143 | -0.0129** | -0.0111 | -0.0131** | -0.0131** | -0.0220** | -0.0206** | -0.0179* |
| | (0.0122) | (0.0060) | (0.0134) | (0.0064) | (0.0064) | (0.0086) | (0.0089) | (0.0091) |
| Spring | | | -0.0144 | -0.0145** | -0.0210*** | | -0.0207** | -0.0172 |
| | | | (0.0127) | (0.0062) | (0.0073) | | (0.0087) | (0.0109) |
| Summer | | | -0.0288* | -0.0259*** | -0.0206*** | | -0.0070 | -0.0147 |
| | | | (0.0167) | (0.0091) | (0.0078) | | (0.0129) | (0.0116) |
| Fall | | | 0.0105 | 0.0009 | 0.0043 | | -0.0355*** | -0.0223 |
| | | | (0.0192) | (0.0096) | (0.0101) | | (0.0126) | (0.0143) |
| N | 55,818 | 52,906 | 55,818 | 52,906 | 52,906 | 12,170 | 12,170 | 12,170 |
| Adj. R. sq. | 0.4105 | 0.8727 | 0.4105 | 0.8727 | 0.8727 | 0.9593 | 0.9593 | 0.9594 |
| Controls | | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ |
| Interactions | | | Two-way | Three-way | Two-way | | Three-way | Two-way |
| SAD, not HoN | | | | | ✓ | | | ✓ |
| Fixed effects | MYQ | MYQ | MYQ | MYQ | MYQ | YQ | YQ | YQ |
| Zip code FE | ✓ | ✓ | ✓ | ✓ | ✓ | | | |
| Unit FE | | | | | | ✓ | ✓ | ✓ |

**Notes:** The table reports marginal effects at the means from regressions of the log of the sale price on cloud cover. Weather variables are computed as the four-day moving averages prior to the sale. All variables are in natural logarithms. HoN denotes hours of night. MYQ and YQ refer to municipality-by-year-quarter and year-by-quarter fixed effects, respectively. Weather controls include maximum temperature, wind speed, and their seasonal monthly averages. Additional controls include buyer age, mortgage rate, an indicator for apartments, an interaction between apartment status and unit size, an indicator for non-co-op units, and an interaction between lot size and a non-apartment indicator. The three-way interaction refers to the interaction between cloud cover, precipitation, and hours of night. SAD refers to an adjusted version of the seasonal affective disorder variable from Kamstra et al. (2003), defined as the log of hours of night truncated at zero in spring and summer. Standard errors are one-way clustered at the three-digit zip code-by-year level and reported in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

do not favor this truncation approach. Because cloud cover is measured over a short, four-day window, the risk of confounding with seasonal affective disorder is limited. It is more plausible that short-term exposure to cloud cover has different implications in spring, summer, and fall. Restricting the effect of daylight hours to only the fall imposes an unnecessarily rigid seasonal structure.

### B.1.2 Seasonal interactions

Our main results (Table 2) present pooled marginal effects at the means (MEMs), as well as seasonal MEMs evaluated at seasonal means of precipitation and hours of night. However, the preferred models impose a restriction: the coefficients on cloud cover and its interactions in equation (1) ($\beta_1$, $\beta_2$, $\beta_3$) are fixed across seasons and do not allow for season-specific sensitivity. To test whether our results are robust to a more flexible functional form, we extend model (1) by interacting cloud cover—and its interactions with precipitation and hours of night—with seasonal indicators, as specified in:

$$\begin{aligned} P_{it} = \alpha &+ \sum_{s \in S} \mathbb{I}_s \times (\beta_{1s}\mathrm{CC}_{jt}^{MA} + \beta_{2s}\mathrm{CC}_{jt}^{MA} \times \mathrm{Prec}_{jt}^{MA} + \beta_{3s}\mathrm{CC}_{jt}^{MA} \times \mathrm{HoN}_{jt}) \\ &+ \beta_4\mathrm{Prec}_{jt}^{MA} + \beta_5\mathrm{HoN}_{jt} + \beta_6\mathrm{Prec}_{jt}^{MA} \times \mathrm{HoN}_{jt} \\ &+ \beta_7\mathrm{PosMaxTemp}_{jt}^{MA} + \beta_8\mathrm{NegMaxTemp}_{jt}^{MA} + \beta_9\mathrm{Wind}_{jt}^{MA} \\ &+ \mathbf{W}_{jm}\beta_{\mathbf{W}} + \beta_{10}\mathrm{MortgageRate}_t + \mathbf{X}_i\beta_{\mathbf{X}} + \mu_{it} + \mathrm{Zip}_j + \varepsilon_{it}, \end{aligned} \tag{B.1}$$

where $\mathbb{I}_s$ is an indicator for season $s \in \{\text{spring, summer, fall}\}$. We estimate this specification both with and without housing unit fixed effects.

Results are presented in Table B.2, along with tests of differences across seasonal MEMs. In the cross-sectional results (columns 1–4), we find the estimates are somewhat sensitive to allowing seasonal flexibility. For example, in column (3), the spring MEM is no longer statistically significant at the 10% level, although its magnitude is similar. The summer MEM is more than halved and becomes insignificant, while the fall MEM reverses sign but remains insignificant. Additionally, none of the seasonal MEMs are statistically different from each other.

In contrast, the unit fixed effects specification (column 5), our preferred model, is more stable under the seasonal interaction extension. The spring MEM roughly doubles in size and remains significant at the 5% level; the fall MEM retains a similar magnitude and becomes significant at the 10% level. The summer MEM remains small and statistically insignificant. Moreover, we find that the spring MEM is significantly different from the summer MEM, but not from the fall, and there is no significant difference between the summer and fall MEMs.

Table B.2: Effects of cloud cover on log of home prices, with seasonal interactions

| | Cross-section | | | | Repeat sales | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Panel A: Marginal effects at the means, pooled and by season | | | | | | |
| Spring | -0.0293* | -0.0389*** | -0.0123 | -0.0083 | -0.0410** | -0.0380** |
| | (0.0151) | (0.0120) | (0.0116) | (0.0116) | (0.0173) | (0.0167) |
| Summer | 0.0439*** | -0.0102 | -0.0136 | -0.0155 | 0.0104 | 0.0081 |
| | (0.0152) | (0.0112) | (0.0112) | (0.0112) | (0.0167) | (0.0159) |
| Fall | 0.0032 | 0.0066 | -0.0078 | -0.0048 | -0.0254* | -0.0171 |
| | (0.0139) | (0.0107) | (0.0108) | (0.0108) | (0.0149) | (0.0145) |
| N | 52,911 | 52,909 | 52,906 | 52,906 | 12,170 | 11,363 |
| Adj. R. sq. | 0.7788 | 0.8712 | 0.8730 | 0.8737 | 0.9594 | 0.9622 |
| Fixed effects | MY & MQ | MY & MQ | MYQ | MYQ & MDW | YQ | YQ |
| Zip code FE | | ✓ | ✓ | ✓ | | |
| Unit FE | | | | | ✓ | ✓ |
| Holding time (weeks) | | | | | | ≥52 |
| Panel B: joint F-tests of cloud cover and its interactions | | | | | | |
| F-stat. (across) | 5.5451*** | 4.5128*** | 3.8891*** | 3.6512*** | 1.7815* | 1.2694 |
| F-stat. (spring) | 6.6863*** | 5.5843*** | 0.5545 | 0.2629 | 2.0196 | 1.7699 |
| F-stat. (summer) | 5.0334*** | 6.4261*** | 9.5842*** | 8.7031*** | 1.9841 | 0.9785 |
| F-stat. (fall) | 4.0120*** | 1.7122 | 0.9271 | 1.4026 | 1.3777 | 1.0947 |
| Panel C: testing equality of marginal effects between seasons | | | | | | |
| Spring vs. summer | -0.0732*** | -0.0287* | 0.0013 | 0.0072 | -0.0514** | -0.0461** |
| | (0.0215) | (0.0163) | (0.0161) | (0.0161) | (0.0239) | (0.0230) |
| Spring vs. fall | -0.0325 | -0.0455*** | -0.0045 | -0.0035 | -0.0156 | -0.0209 |
| | (0.0204) | (0.0154) | (0.0152) | (0.0152) | (0.0229) | (0.0222) |
| Summer vs. fall | 0.0406* | -0.0168 | -0.0058 | -0.0107 | 0.0358 | 0.0252 |
| | (0.0213) | (0.0159) | (0.0161) | (0.0161) | (0.0230) | (0.0219) |

**Notes:** The table reports results from regressions of the log of sale prices on cloud cover and controls, where cloud cover and its interactions are interacted with seasonal dummies. Panel B shows the F-statistic and p-value from a joint test of significance for the cloud cover terms within each season. Panel C tests for equality between seasonal marginal effects—for example, testing whether the spring MEM equals the summer MEM involves taking the difference between the two (e.g., -0.0732 in column (1)). All regressions include weather controls (maximum temperature, wind speed, and their seasonal monthly averages), mortgage rate, and buyer age. Fixed effects are denoted as follows: M = municipality, Y = year, Q = quarter, and DW = day-of-week; MYQ thus refers to municipality-by-year-by-quarter fixed effects. Cross-sectional models also control for property attributes: size, an apartment indicator, their interaction, a non-co-op indicator, and its interaction with lot size. Standard errors are one-way clustered at the three-digit zip code-by-year level and reported in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

### B.1.3 Adjusting the moving average window

Our models rely on a four-day moving average of weather conditions prior to the sale, a choice informed by both institutional features of the housing market and empirical patterns. To assess the sensitivity of our results to this window, we re-estimate the models using shorter (two-day) and longer (six-day) windows. We avoid extending the window further, as doing so would begin to capture broader seasonal variation, overlapping with our seasonal controls. Results are shown in Table B.3.

In the cross-sectional models, shortening the window increases the pooled MEM and reduces the summer MEM, though all effects remain significant at the 1% level—except for fall, which remains insignificant. Lengthening the window produces a similar pooled effect (significant at the 10% level) but yields a stronger summer MEM (0.0350, significant at the 1% level).

For the repeat sales models, shortening the window reduces the magnitude of MEMs and renders them statistically insignificant. Extending the window, by contrast, results in MEMs similar to the main specification. However, when applying the same holding time restriction as in the baseline, only the fall MEM remains significant (-0.0280, significant at the 10% level).

Changing the moving average window affects the analysis along two key dimensions. First, expanding the window increases its correlation with seasonal controls, introducing potential bias in unknown directions; reducing the window weakens this correlation. Second, averaging over more days may dilute the relevance of weather at key decision points, introducing noise and possibly amplifying the estimates while reducing their precision. Conversely, shortening the window risks missing influential weather conditions altogether, which may attenuate the measured effect and compromise our ability to identify the relationship of interest.

### B.1.4 Shorter TOM

As an alternative to adjusting the moving average window, we increase the likelihood of capturing cloud cover during relevant open house days by imposing restrictions on time-on-market (TOM). Shortening TOM ensures that open houses occur closer to the sale date, making it more likely that they fall within the four-day window prior to the sale. The sample's TOM ranges from 7 to 22 days; we test restrictions at 18, 14, and 10 days. Results in Table B.4 show that the effect strengthens as TOM decreases, consistent with more accurate measurement of relevant cloud cover. The most striking result appears in the repeat sales sample restricted to TOM $\leq$ 10 days: the pooled MEM is -0.0345, significant at the 5% level—nearly double the magnitude of the estimate in Table 2.

Table B.3: Sensitivity to changing the moving average window

| | MA(2) | | | MA(6) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Marginal effects at the means, pooled and by season | | | | | | |
| Pooled | -0.0145*** | -0.0103 | -0.0113* | -0.0140* | -0.0195* | -0.0162* |
| | (0.0051) | (0.0071) | (0.0068) | (0.0074) | (0.0103) | (0.0098) |
| Spring | -0.0143*** | -0.0099 | -0.0100 | -0.0164** | -0.0207** | -0.0171* |
| | (0.0049) | (0.0068) | (0.0064) | (0.0072) | (0.0101) | (0.0095) |
| Summer | -0.0212*** | -0.0077 | -0.0077 | -0.0356*** | -0.0029 | -0.0030 |
| | (0.0070) | (0.0097) | (0.0091) | (0.0102) | (0.0140) | (0.0133) |
| Fall | -0.0080 | -0.0136 | -0.0170* | 0.0106 | -0.0362** | -0.0293** |
| | (0.0069) | (0.0099) | (0.0098) | (0.0104) | (0.0141) | (0.0140) |
| N | 52,906 | 12,170 | 11,363 | 52,906 | 12,170 | 11,363 |
| Adj. R. sq. | 0.8727 | 0.9593 | 0.9620 | 0.8727 | 0.9593 | 0.9621 |
| Fixed effects | MYQ | YQ | YQ | MYQ | YQ | YQ |
| Zip code FE | ✓ | | | ✓ | | |
| Unit FE | | ✓ | ✓ | | ✓ | ✓ |
| Holding time (weeks) | | | ≥52 | | | ≥52 |

**Notes:** The table reports marginal effects at the means from regressions of the log of sale price on cloud cover and control variables. Columns (1)–(3) use weather variables averaged over the two days prior to sale (MA(2)), while columns (4)–(6) use six-day averages (MA(6)). Fixed effects include municipality-by-year-by-quarter (MYQ) and year-by-quarter (YQ). All regressions control for maximum temperature, wind speed, and their seasonal monthly averages, as well as age and mortgage rate. Cross-sectional models include controls for housing attributes: unit size, apartment indicator, interaction of size and apartment indicator, non-co-op indicator, and interaction of lot size and non-apartment indicator. Standard errors are clustered by three-digit zip code-by-year and shown in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table B.4: Sensitivity to restricting TOM in the sample

| TOM | ≤18 | ≤14 | ≤10 | ≤18 | ≤14 | ≤10 |
|---|---|---|---|---|---|---|
| Marginal effects at the means, pooled and by season | | | | | | |
| Pooled | -0.0159** | -0.0173** | -0.0186** | -0.0197** | -0.0218** | -0.0337 |
| | (0.0065) | (0.0068) | (0.0082) | (0.0095) | (0.0097) | (0.0138) |
| Spring | -0.0181*** | -0.0188*** | -0.0209*** | -0.0202** | -0.0222** | -0.0325** |
| | (0.0063) | (0.0066) | (0.0079) | (0.0092) | (0.0094) | (0.0133) |
| Summer | -0.0337*** | -0.0344*** | -0.0355*** | -0.0126 | -0.0134 | -0.0190 |
| | (0.0090) | (0.0093) | (0.0109) | (0.0128) | (0.0133) | (0.0178) |
| Fall | 0.0048 | 0.0021 | 0.0017 | -0.0267** | -0.0303** | -0.0518*** |
| | (0.0092) | (0.0096) | (0.0113) | (0.0129) | (0.0135) | (0.0197) |
| N | 50,359 | 46,791 | 33,032 | 11,104 | 9,754 | 5,366 |
| Adj. R. sq. | 0.8732 | 0.8738 | 0.8735 | 0.9585 | 0.9589 | 0.9556 |
| Fixed effects | MYQ | MYQ | MYQ | YQ | YQ | YQ |
| Zip code FE | ✓ | ✓ | ✓ | | | |
| Unit FE | | | | ✓ | ✓ | ✓ |

**Notes:** The table reports marginal effects at the means from regressions of the log of sale price on cloud cover. The sample is restricted based on the time-on-market (TOM), with weather variables measured as four-day moving averages prior to the sale. Fixed effects include municipality-by-year-by-quarter (MYQ) and year-by-quarter (YQ). All regressions control for maximum temperature, wind speed, and their seasonal monthly averages, as well as age and mortgage rate. Cross-sectional models additionally control for: property size, an indicator for apartment units, the interaction between size and apartment status, an indicator for non-co-op units, and the interaction between lot size and a non-apartment indicator. Standard errors are one-way clustered at the three-digit zip code-by-year level and reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

## B.2 Placebo test of the effect of cloud cover during open houses

Table B.5: Placebo test, cross-section

| Coef. estimates | | | Marginal effects at the means | | | |
|---|---|---|---|---|---|---|
| CC | CC x Prec. | CC x HoN | Pooled | Spring | Summer | Fall |
| **Replace all** | | | | | | |
| 0.00265 | -0.00022 | -0.00108 | 0.00001 | 0.00006 | 0.00000 | -0.00003 |
| (0.03162) | (0.00580) | (0.01377) | (0.00646) | (0.00608) | (0.00660) | (0.00691) |
| **Replace cloud cover** | | | | | | |
| -0.00018 | 0.00011 | 0.00002 | -0.00003 | -0.00004 | -0.00003 | -0.00001 |
| (0.02696) | (0.00510) | (0.01156) | (0.00462) | (0.00468) | (0.00604) | (0.00633) |
| **Replace precipitation** | | | | | | |
| -0.09133 | -0.00020 | 0.03727 | -0.00785 | -0.00924 | -0.02008 | 0.00614 |
| (0.00489) | (0.00510) | (0.00015) | (0.00005) | (0.00006) | (0.00007) | (0.00008) |

**Notes:** The table presents results from re-estimating model (1) after randomly reassigning weather variables across observations. Weather variables are randomly drawn with replacement from the time series of four-day moving averages, excluding the winter season. Reported coefficients are the averages across 1,000 repetitions, with standard deviations of the estimated coefficients shown in parentheses. When replacing all weather variables, each observation receives a new full set of weather values—including cloud cover, maximum temperature, wind speed, and their corresponding seasonal controls—via row-wise replacement. When replacing a single weather variable, only that variable and its seasonal control are replaced (e.g., cloud cover and its seasonal control). Fixed effects include municipality-by-year-by-quarter (MYQ). All regressions control for age, mortgage rate, maximum temperature, wind speed, and their seasonal monthly averages. Additional controls include property size, an indicator for apartment units, the interaction between size and apartment status, an indicator for non-co-op units, and the interaction between lot size and a non-apartment indicator.

Table B.6: Placebo test, repeat sales sample

| Coef. estimates | | | Marginal effects at the means | | | |
|---|---|---|---|---|---|---|
| CC | CC x Prec. | CC x HoN | All | Spring | Summer | Fall |
| **Replace all** | | | | | | |
| 0.00016 | 0.00045 | -0.00017 | 0.00020 | 0.00011 | 0.00022 | 0.00028 |
| (0.04719) | (0.00833) | (0.02037) | (0.00899) | (0.00846) | (0.00919) | (0.00965) |
| **Replace cloud cover** | | | | | | |
| 0.00106 | -0.00018 | -0.00036 | 0.00009 | 0.00012 | 0.00019 | -0.00006 |
| (0.04055) | (0.00728) | (0.01746) | (0.00647) | (0.00663) | (0.00865) | (0.00923) |
| **Replace precipitation** | | | | | | |
| 0.03587 | 0.00046 | -0.02167 | -0.01221 | -0.01172 | -0.00519 | -0.02049 |
| (0.00670) | (0.00688) | (0.00050) | (0.00019) | (0.00020) | (0.00024) | (0.00028) |

**Notes:** The table reports results from re-estimating model (1) after randomly reassigning weather variables across observations. Weather values are drawn with replacement from the time series of four-day moving averages, excluding winter observations. Each specification is estimated 1,000 times; reported coefficients are the means across repetitions, with standard deviations in parentheses. When all weather variables are replaced, this involves row-wise substitution of the full set—including maximum temperature, wind speed, cloud cover, and their corresponding seasonal controls. When a single weather variable is replaced, only that variable and its associated seasonal control are substituted (e.g., cloud cover and its seasonal control). The regressions include unit and year-by-quarter fixed effects, along with controls for age, mortgage rate, maximum temperature, wind speed, and their seasonal monthly averages.

## B.3 Heterogeneity effects of cloud cover during open houses

Table B.7: Segmented regressions on apartments and non-apartments

| | Apartments | | | Non-apartments | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Marginal effects at the means, pooled and by season | | | | | | |
| Pooled | -0.0062 | -0.0234*** | -0.0199** | -0.0150 | -0.0154 | -0.0083 |
| | (0.0071) | (0.0088) | (0.0085) | (0.0122) | (0.0307) | (0.0298) |
| Spring | -0.0076 | -0.0249*** | -0.0211** | -0.0164 | -0.0080 | 0.0030 |
| | (0.0068) | (0.0086) | (0.0082) | (0.0119) | (0.0300) | (0.0294) |
| Summer | -0.0159 | -0.0232* | -0.0220* | -0.0302* | 0.0188 | 0.0320 |
| | (0.0097) | (0.0120) | (0.0120) | (0.0173) | (0.0415) | (0.0397) |
| Fall | 0.0054 | -0.0218* | -0.0162 | 0.0014 | -0.0593 | -0.0624 |
| | (0.0100) | (0.0122) | (0.0119) | (0.0189) | (0.0405) | (0.0389) |
| N | 38,991 | 10,172 | 9,522 | 13,908 | 1,996 | 1,839 |
| Adj. R. sq. | 0.8727 | 0.9631 | 0.9658 | 0.8769 | 0.9460 | 0.9491 |
| Fixed effects | MYQ | YQ | YQ | MYQ | YQ | YQ |
| Zip code FE | ✓ | | | ✓ | | |
| Unit FE | | ✓ | ✓ | | ✓ | ✓ |
| Holding time (weeks) | | | ≥52 | | | ≥52 |

**Notes:** The table reports results from regressions of the log of the sale price on cloud cover. Estimates are shown for subsamples of apartments and non-apartments. Marginal effects are evaluated at the means of the full sample, both overall and by season, without conditioning on property type. Weather variables are measured as four-day moving averages prior to the sale. Fixed effects are abbreviated as follows: M = municipality, Y = year, Q = quarter, and DW = day-of-the-week. MYQ denotes municipality-by-year-by-quarter fixed effects. All regressions control for weather variables (maximum temperature and wind speed) and their seasonal monthly averages, as well as buyer age and the mortgage rate. Covariates differ across property types. For apartments, the regressions include an indicator for non-cooperative units. For non-apartments, the regressions include lot size and housing type indicators for row houses and semi-detached houses (with detached units as the omitted category). Standard errors are clustered at the three-digit zip code-by-year level and are shown in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

To examine heterogeneity across buyer type, we augment model (1) by interacting the moving average of cloud cover, and its interactions with precipitation and hours of night, with an indicator variable for each of the buyer groups examined. For instance, when estimating the model separating between single and multiple buyers, the indicator takes value one for transactions with multiple buyers and else zero. Note that when estimating models that separate between the effect of household composition, we include only transactions where buyers belong to the same household, because the number of adults and children is likely not informative when buyers come from different households.

Table B.8: Buyer heterogeneity, unit FE

| | Buyers | Adults | Children | Uni. | Wealth | Income | Gender | Age | First-time |
|---|---|---|---|---|---|---|---|---|---|
| Marginal effects at the means, pooled and by season | | | | | | | | | |
| Panel A: | >1 | >1 | >0 | Yes | >median | >median | Female | >median | Yes |
| Pooled | -0.0155 | -0.0239* | -0.0479** | -0.0220** | -0.0235* | -0.0298** | -0.0392** | -0.0202 | -0.0170* |
| | (0.0120) | (0.0131) | (0.0199) | (0.0106) | (0.0127) | (0.0124) | (0.0158) | (0.0140) | (0.0103) |
| Spring | -0.0163 | -0.0237* | -0.0495** | -0.0232** | -0.0242* | -0.0312** | -0.0366** | -0.0207 | -0.0184* |
| | (0.0118) | (0.0127) | (0.0200) | (0.0104) | (0.0127) | (0.0123) | (0.0157) | (0.0139) | (0.0102) |
| Summer | -0.0091 | -0.0168 | -0.0471** | -0.0158 | -0.0126 | -0.0247 | -0.0175 | -0.0121 | -0.0118 |
| | (0.0151) | (0.0172) | (0.0237) | (0.0138) | (0.0156) | (0.0153) | (0.0200) | (0.0167) | (0.0134) |
| Fall | -0.0214 | -0.0317* | -0.0469** | -0.0272** | -0.0344** | -0.0336** | -0.0673*** | -0.0285* | -0.0210 |
| | (0.0142) | (0.0165) | (0.0222) | (0.0132) | (0.0154) | (0.0151) | (0.0216) | (0.0166) | 0.0131 |
| Panel B: | 1 | 1 | 0 | No | ≤median | ≤median | Male | ≤median | No |
| Pooled | -0.0232** | -0.0411** | -0.0232* | -0.0121 | -0.0160 | -0.0119 | -0.0302 | -0.0188* | -0.0222* |
| | (0.0108) | (0.0159) | (0.0120) | (0.0159) | (0.0099) | (0.0102) | (0.0202) | (0.0096) | (0.0120) |
| Spring | -0.0245** | -0.0418*** | -0.0227* | -0.0122 | -0.0175* | -0.0127 | -0.0278 | -0.0204** | -0.0232* |
| | (0.0108) | (0.0160) | (0.0116) | (0.0160) | (0.0098) | (0.0101) | (0.0202) | (0.0095) | (0.0119) |
| Summer | -0.0170 | -0.0334* | -0.0140 | -0.0095 | -0.0118 | -0.0034 | -0.0153 | -0.0122 | -0.0148 |
| | (0.0136) | (0.0194) | (0.0160) | (0.0184) | (0.0131) | (0.0135) | (0.0248) | (0.0130) | (0.0149) |
| Fall | -0.0281** | -0.0487*** | -0.0337** | -0.0150 | -0.0186 | -0.0202 | -0.0503** | -0.0238* | -0.0288* |
| | (0.0135) | (0.0187) | (0.0156) | (0.0180) | (0.0128) | (0.0128) | (0.0232) | (0.0124) | (0.0149) |
| N | 11,865 | 7,740 | 7,740 | 11,419 | 11,631 | 11,631 | 4,348 | 11,631 | 11,631 |
| Adj. R. sq. | 0.9608 | 0.9611 | 0.9612 | 0.9609 | 0.9607 | 0.9607 | 0.9513 | 0.9607 | 0.9607 |
| Fixed effects | YQ | YQ | YQ | YQ | YQ | YQ | YQ | YQ | YQ |
| Unit FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

**Notes:** The table reports marginal effects at the means from regressions of the log of the sale price on cloud cover. For each buyer characteristic, the moving average of cloud cover and its interactions with precipitation and hours of night are interacted with an indicator for whether the buyers fall into the respective group. *Buyers* refers to the number of buyers on the contract. *Adults* and *Children* are based on household composition, using only transactions in which all buyers belong to the same household; others are excluded. *Adults* refers to household members aged 18 or older, while *Children* refers to those aged 17 or younger. *Uni.* indicates whether any buyer holds a university degree. *Wealth* and *Income* refer to total gross values across buyers, deflated to 2015 using the consumer price index. *Gender* captures the buyer's gender in single-buyer transactions only. *Age* refers to the average age of buyers. *First-time* indicates whether none of the buyers owns a home, based on the taxable value of their primary residence. Effects are evaluated at the sample means and by season. All weather variables are four-day moving averages prior to the sale. Regressions include year-by-quarter (YQ) fixed effects, weather controls (maximum temperature, wind speed, and their seasonal monthly averages), housing unit age, and the mortgage rate. Standard errors are one-way clustered at the three-digit zip code-by-year level and are reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

# C Potential mechanisms

## C.1 Mood bias

Table C.1: Marginal effects of cloud cover on sale price: Cloud cover similarity during open houses and sale day

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Marginal effects at the means, pooled and by season | | | | | |
| $\lvert CC^{DOS} - CC^{MA}\rvert$ | ≤0.8 | ≤0.7 | ≤0.6 | ≤0.5 | ≤0.4 |
| Pooled | -0.0162* | -0.0211** | -0.0245** | -0.0287*** | -0.0320*** |
| | (0.0093) | (0.0097) | (0.0103) | (0.0105) | (0.0112) |
| Spring | -0.0166* | -0.0218** | -0.0252** | -0.0294*** | -0.0322*** |
| | (0.0091) | (0.0095) | (0.0101) | (0.0103) | (0.0110) |
| Summer | -0.0119 | -0.0166 | -0.0187 | -0.0216 | -0.0267* |
| | (0.0125) | (0.0130) | (0.0135) | (0.0138) | (0.0141) |
| Fall | -0.0204 | -0.0252** | -0.0301** | -0.0356*** | -0.0370*** |
| | (0.0126) | (0.0127) | (0.0132) | (0.0136) | (0.0143) |
| N | 12,170 | 12,170 | 12,170 | 12,170 | 12,170 |
| Adj. R. sq. | 0.9593 | 0.9593 | 0.9593 | 0.9593 | 0.9593 |
| Fixed effects | YQ | YQ | YQ | YQ | YQ |
| Unit FE | ✓ | ✓ | ✓ | ✓ | ✓ |

**Notes:** The table shows marginal effects at the means from regressing log of the selling price on the cloud cover. The moving average of cloud cover, and its interactions with precipitation and hours of night, are interacted with an indicator taking the value one if the absolute difference between the cloud cover on the day of the sale ($CC^{DOS}$) and during the open houses ($CC^{MA}$) is less than a threshold value $\tau \in \{0.4, 0.5, 0.6, 0.7, 0.8\}$, and else zero. Weather variables are the moving averages of the four days prior to the sale. YQ denotes the year-by-quarter fixed effects. All regressions include the weather controls maximum temperature and wind speed and seasonal monthly averages. All regressions control for age and mortgage rate. Standard errors are one-way clustered on three-digit zip codes-by-year, and are given in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

Table C.2: Marginal effects of cloud cover on sale price: Cloud cover prior to the open houses

| MA window prior to open houses | 4 days | 6 days | 8 days | 10 days | 12 days | 14 days |
|---|---|---|---|---|---|---|
| Marginal effects at the means, pooled and by season | | | | | | |
| Pooled | -0.0169* | -0.0101 | -0.0068 | -0.0061 | 0.0041 | 0.0026 |
| | (0.0099) | (0.0114) | (0.0121) | (0.0126) | (0.0136) | (0.0150) |
| Spring | -0.0144 | -0.0091 | -0.0064 | -0.0046 | 0.0052 | 0.0032 |
| | (0.0092) | (0.0110) | (0.0120) | (0.0128) | (0.0139) | (0.0154) |
| Summer | 0.0005 | 0.0132 | 0.0252 | 0.0257 | 0.0330* | 0.0206 |
| | (0.0132) | (0.0153) | (0.0158) | (0.0166) | (0.0177) | (0.0187) |
| Fall | -0.0393*** | -0.0367** | -0.0421** | -0.0426** | -0.0288 | -0.0178 |
| | (0.0136) | (0.0151) | (0.0165) | (0.0177) | (0.0191) | (0.0213) |
| N | 12,170 | 12,170 | 12,170 | 12,170 | 12,170 | 12,170 |
| Adj. R. sq. | 0.9593 | 0.9593 | 0.9593 | 0.9593 | 0.9593 | 0.9592 |
| Fixed effects | YQ | YQ | YQ | YQ | YQ | YQ |
| Unit FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

**Notes:** The table reports marginal effects at the means from regressions of the log of the sale price on cloud cover. All weather variables are now measured as moving averages over $x \in \{4, 6, 8, 10, 12, 14\}$ days *prior* to the open house dates, i.e., they cover the period 5 to $(5 - x)$ days prior to the sale. YQ refers to year-by-quarter fixed effects. All regressions include weather controls—maximum temperature and wind speed—as well as their seasonal monthly averages. Additional controls include the age of the housing unit and the mortgage rate. Standard errors are one-way clustered at the three-digit zip code-by-year level and are reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

## C.2 Projection bias

Table C.3: Impact of open house cloud cover on early resale probability (within 1-4 years)

| Holding time | $\leq$4yrs | $\leq$3yrs | $\leq$2yrs | $\leq$1yrs |
|---|---|---|---|---|
| Marginal effects at the means, pooled and by season | | | | |
| Pooled | 0.0309 | 0.0734 | 0.0387 | 0.0407 |
| | (0.0479) | (0.0562) | (0.0508) | (0.0275) |
| Spring | 0.0397 | 0.0756 | 0.0397 | 0.0393 |
| | (0.0460) | (0.0541) | (0.0490) | (0.0270) |
| Summer | 0.0396 | 0.0674 | 0.0275 | 0.0441 |
| | (0.0614) | (0.0748) | (0.0697) | (0.0410) |
| Fall | 0.0101 | 0.0766 | 0.0487 | 0.0392 |
| | (0.0738) | (0.0768) | (0.0662) | (0.0343) |
| N | 5,992 | 5,992 | 5,992 | 5,992 |
| Adj. R. sq. | 0.1394 | 0.1805 | 0.1740 | 0.1387 |
| Fixed effects | MYQ | MYQ | MYQ | MYQ |
| Zip code FE | ✓ | ✓ | ✓ | ✓ |
| Unit FE | | | | |

**Notes:** The table presents marginal effects at the means from regressions of an indicator variable—equal to one if the housing unit is resold within 1 to 4 years—on cloud cover during the open house period at the time of purchase. Holding time refers to the duration for which the buyer (homeowner) retains ownership before reselling. Weather variables are calculated as four-day moving averages prior to the initial sale. The regressions include municipality-by-year-by-quarter (MYQ) fixed effects, as well as controls for maximum temperature and wind speed and their seasonal monthly averages. Additional controls include property age, mortgage rate, living area, an apartment indicator, the interaction between size and apartment status, a non-co-op indicator, and the interaction between lot size and a non-apartment indicator. Standard errors are clustered at the three-digit zip code-by-year level and are reported in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

## C.3 Salience

Table C.4: Marginal effects of cloud cover on sale price: cloud cover during open houses relative to prior period

| Window prior to open houses | 4 days | 6 days | 8 days | 10 days |
|---|---|---|---|---|
| Panel A: Lower cloud cover during open houses than prior to open houses | | | | |
| Pooled | -0.0129 | -0.0041 | -0.0194 | -0.0268** |
| | (0.0118) | (0.0119) | (0.0124) | (0.0117) |
| Spring | -0.0137 | -0.0039 | -0.0213* | -0.0281** |
| | (0.0118) | (0.0119) | (0.0126) | (0.0117) |
| Summer | 0.0003 | 0.0071 | -0.0082 | -0.0177 |
| | (0.0146) | (0.0149) | (0.0156) | (0.0152) |
| Fall | -0.0268* | -0.0171 | -0.0301* | -0.0358** |
| | (0.0156) | (0.0159) | (0.0165) | (0.0158) |
| Panel B: Higher cloud cover during open houses than prior to open houses | | | | |
| Pooled | -0.0254* | -0.0407** | -0.0319** | -0.0249 |
| | (0.0143) | (0.0164) | (0.0159) | (0.0178) |
| Spring | -0.0268* | -0.0433*** | -0.0332** | -0.0254 |
| | (0.0143) | (0.0166) | (0.0160) | (0.0182) |
| Summer | -0.0159 | -0.0318* | -0.0227 | -0.0165 |
| | (0.0174) | (0.0188) | (0.0182) | (0.0203) |
| Fall | -0.0334** | -0.0462** | -0.0393** | -0.0327* |
| | (0.0160) | (0.0179) | (0.0176) | (0.0187) |
| N | 12,170 | 12,170 | 12,170 | 12,170 |
| Adj. R. sq. | 0.9593 | 0.9593 | 0.9593 | 0.9593 |
| Fixed effects | YQ | YQ | YQ | YQ |
| Unit FE | ✓ | ✓ | ✓ | ✓ |

**Notes:** The table reports marginal effects at the means from regressions of the log of the sale price on cloud cover. Weather variables are measured as moving averages over the four days prior to the sale. The moving average of cloud cover, along with its interactions with precipitation and hours of night, is interacted with an indicator variable equal to one if the cloud cover during the open house period is lower (Panel A) or higher (Panel B) than the average cloud cover over the $x \in \{4, 6, 8, 10\}$ days preceding the open house period, and zero otherwise. YQ refers to year-by-quarter fixed effects. All regressions include weather controls—maximum temperature and wind speed—as well as their seasonal monthly averages. Additional controls include housing unit age and the mortgage rate. Standard errors are one-way clustered at the three-digit zip code-by-year level and are reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table C.5: Dropping older vintages

| Year built | ≥1950 | ≥1960 | ≥1970 | ≥1980 | ≥1990 |
|---|---|---|---|---|---|
| Panel A: All unit types | | | | | |
| Pooled | -0.0237** | -0.0281** | -0.0282** | -0.0427*** | -0.0346** |
| | (0.0105) | (0.0120) | (0.0139) | (0.0158) | (0.0158) |
| Spring | -0.0238** | -0.0273** | -0.0272** | -0.0421*** | -0.0326** |
| | (0.0103) | (0.0117) | (0.0136) | (0.0154) | (0.0155) |
| Summer | -0.0200 | -0.0316* | -0.0401** | -0.0610*** | -0.0538*** |
| | (0.0141) | (0.0163) | (0.0185) | (0.0205) | (0.0208) |
| Fall | -0.0272* | -0.0257 | -0.0173 | -0.0250 | -0.0178 |
| | (0.0139) | (0.0159) | (0.0183) | (0.0209) | (0.0218) |
| N | 8,847 | 6,773 | 5,114 | 3,763 | 2,735 |
| Adj. R. sq. | 0.9603 | 0.9639 | 0.9685 | 0.9705 | 0.9768 |
| Fixed effects | YQ | YQ | YQ | YQ | YQ |
| Unit FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Panel B: Apartments | | | | | |
| Pooled | -0.0303*** | -0.0389*** | -0.0376*** | -0.0517*** | -0.0431** |
| | (0.0105) | (0.0117) | (0.0143) | (0.0166) | (0.0171) |
| Spring | -0.0315*** | -0.0388*** | -0.0368*** | -0.0514*** | -0.0427** |
| | (0.0102) | (0.0114) | (0.0140) | (0.0163) | (0.0169) |
| Summer | -0.0355** | -0.0537*** | -0.0567*** | -0.0759*** | -0.0687*** |
| | (0.0145) | (0.0164) | (0.0193) | (0.0220) | (0.0233) |
| Fall | -0.0233 | -0.0241 | -0.0191 | -0.0268 | -0.0172 |
| | (0.0142) | (0.0162) | (0.0191) | (0.0216) | (0.0223) |
| N | 7,126 | 5,295 | 3,987 | 2,988 | 2,292 |
| Adj. R. sq. | 0.9605 | 0.9655 | 0.9696 | 0.9706 | 0.9750 |
| Fixed effects | YQ | YQ | YQ | YQ | YQ |
| Unit FE | ✓ | ✓ | ✓ | ✓ | ✓ |

**Notes:** The table shows marginal effects at the means from regressing log of the selling price on the cloud cover. Panel A reports results from the sample that includes both apartments and non-apartments, and Panel B reports results from the apartments-only subsample. The samples are increasingly restricted by dropping vintages earlier than $\{1950, 1960, 1970, 1980, 1990\}$. Weather variables are the moving averages of the four days prior to the sale. All variables are in natural logarithms. YQ denotes the year-by-quarter fixed effects. All regressions include the weather controls maximum temperature and wind speed and seasonal monthly averages. All regressions control for age and mortgage rate. Standard errors are one-way clustered on three-digit zip codes-by-year, and are given in parenthesis. Significance: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

# D Model extension to the winter season

All estimations in our main analysis exclude the winter season. This choice is motivated by several factors. First, sunshine is generally absent during winter, and even under clear skies, open houses may receive no direct sunlight, introducing measurement noise. Second, winter is an atypical selling season: snow and ice can obscure key property features, reduce accessibility, and alter the perceived environment due to factors like snow cover, snow depth, and icy conditions. Third, housing market activity is generally lower in winter, adding concerns about illiquidity. Collectively, these issues suggest that including winter data may introduce substantial noise.

To assess the effect of including winter, we re-estimate the main model (1) using the full seasonal sample. Results are reported in Table D.1. The repeat sales estimates show a smaller pooled effect relative to our main results—consistent with increased measurement error. Notably, we observe a significant winter effect, which may reflect the correlation between cloud cover and winter-specific factors not captured in the model (e.g., snow or ice conditions).

To account for season-specific variation, we first add a winter dummy ($D_{\text{winter}}$) to the model. The winter coefficient remains large but becomes statistically insignificant, and the pooled effect weakens, remaining marginally significant at the 10% level. Seasonal marginal effects are not statistically significant.

Next, we allow the effect of non-interacted cloud cover to vary in winter by interacting it with the winter dummy, leaving all other interactions unchanged. This adjustment increases the pooled marginal effect relative to the main results, but the spring and fall effects weaken and become only marginally significant.

Finally, we allow all weather variables and their interactions—but not the seasonal controls—to vary by winter (denoted as $\text{Wx}\times D_{\text{wi}}$). This fully interacted specification restores estimates that are both statistically significant and similar in magnitude to our main results (Table 2), suggesting that accounting for winter-specific heterogeneity in weather variables is critical when including winter in the sample.

Table D.1: Model results including the winter season

| | Cross-section | | | | Unit FE | | | |
|---|---|---|---|---|---|---|---|---|
| | | $D_{wi.}$ | $CCxD_{wi.}$ | $WxD_{wi.}$ | | $D_{wi.}$ | $CCxD_{wi.}$ | $WxD_{wi.}$ |
| Marginal effects at the means, pooled and by season | | | | | | | | |
| Pooled | -0.0081 | -0.0073 | -0.0157** | -0.0170** | -0.0152* | -0.0147* | -0.0275*** | -0.0297*** |
| | (0.0059) | (0.0058) | (0.0070) | (0.0071) | (0.0079) | (0.0080) | (0.0094) | (0.0093) |
| Spring | -0.0143** | -0.0122** | -0.0132** | -0.0128** | -0.0135* | -0.0122 | -0.0134* | -0.0155* |
| | (0.0060) | (0.0061) | (0.0061) | (0.0062) | (0.0079) | (0.0081) | (0.0081) | (0.0080) |
| Summer | -0.0283*** | -0.0259*** | -0.0253*** | -0.0256*** | -0.0088 | -0.0071 | -0.0066 | -0.0083 |
| | (0.0087) | (0.0087) | (0.0087) | (0.0088) | (0.0111) | (0.0111) | (0.0111) | (0.0111) |
| Fall | 0.0055 | 0.0072 | 0.0041 | 0.0061 | -0.0192** | -0.0182* | -0.0224** | -0.0245** |
| | (0.0072) | (0.0084) | (0.0086) | (0.0088) | (0.0097) | (0.0110) | (0.0114) | (0.0113) |
| Winter | 0.0137 | 0.0079 | 0.0123 | 0.0085 | -0.0219* | -0.0252 | -0.0210 | -0.0185 |
| | (0.0085) | (0.0130) | (0.0133) | (0.0153) | (0.0113) | (0.0204) | (0.0207) | (0.0218) |
| N | 63,752 | 63,752 | 63,752 | 63,752 | 17,718 | 17,718 | 17,718 | 17,718 |
| Adj. R. sq. | 0.8737 | 0.8737 | 0.8737 | 0.8737 | 0.9588 | 0.9589 | 0.9589 | 0.9589 |
| Fixed effects | MYQ | MYQ | MYQ | MYQ | YQ | YQ | YQ | YQ |
| Zip code FE | ✓ | ✓ | ✓ | ✓ | | | | |

**Notes:** The table reports marginal effects at the means from regressions of the log of sale price on cloud cover, including observations from the winter season. Columns correspond to different extensions of the main specification in Equation (1): Dwi. indicates a winter season dummy; CC×Dwi. refers to the interaction between cloud cover and the winter dummy (excluding interactions with precipitation and hours of night); and $Wx\times D_{wi.}$ includes interactions between all weather variables and the winter dummy. Weather variables are computed as four-day moving averages preceding the sale. Fixed effects include municipality-by-year-by-quarter (MYQ) and year-by-quarter (YQ). All regressions control for maximum temperature, wind speed, and their seasonal monthly averages, as well as unit age and mortgage rate. Cross-sectional regressions additionally control for unit characteristics: living area, an apartment indicator, the interaction between size and apartment status, a non-co-op indicator, and the interaction between lot size and a non-apartment indicator. Standard errors are one-way clustered at the three-digit zip code-by-year level and reported in parentheses.* p<0.1, ** p<0.05, *** p<0.01.

# E Effect of sunshine duration

## E.1 Supplementary weather data

While cloud cover is commonly used to approximate sunshine exposure—largely due to its widespread availability—alternative measures such as sunshine duration can provide useful complementary insights. To supplement the gridded weather data from the Copernicus Climate Change Service, we collect additional weather data from MET Norway's API service, Frost, which provides sub-daily *in-situ* observations from local weather stations.[19] These observations are matched to each transaction based on the nearest available station within a 20-kilometer radius. An exception is the Tryvann station in Oslo, for which we apply a 2-kilometer radius due to its high elevation and limited representativeness for the broader Oslo area.

We retain only observations with quality codes 0, 1, or 2, where 0 indicates the highest quality and 2 signifies minor uncertainty. We further restrict the sample to stations that meet the World Meteorological Organization's site requirements. Since we aim to capture weather during open house events, we use hourly observations recorded between 11:00 AM and 6:00 PM CET and calculate average values within this window.

*Sunshine duration:* Available at both hourly and daily frequencies, this variable measures the number of minutes of sunshine during the previous hour or the total number of sunshine hours for a full day. We use both versions to assess their relationship with cloud cover.

*Cloud cover:* Reported at intervals ranging from one to six hours and available as a daily average, cloud cover is measured on a scale from 0 (clear sky) to 8 (fully overcast) and referred to as the "cloud area fraction." We collect this variable to compare it with sunshine duration.

*Precipitation:* Recorded as the accumulated precipitation over the past hour (in millimeters) at most stations.

*Air temperature:* Measured in degrees Celsius, we prioritize hourly readings. If unavailable, we use observations taken every six hours.

*Wind speed:* We use the highest average (non-gust) wind speed reported during the past hour, measured in meters per second.

To address gaps or inconsistencies in the data, we replace missing values using a four-day moving average prior to the missing observation, provided data are available for all four preceding days. This imputation is repeated up to 14 times to fill gaps of up to two weeks. While this method allows us to retain intra-day weather data during the relevant

[19] *In-situ* weather data are collected directly at the physical location of the weather station, offering more precise and localized information than satellite-based observations.

open house window, these alternative data remain less comprehensive than the Copernicus sample due to limited spatial coverage, intermittent availability, and inconsistent measurement accuracy. Consequently, estimates based on these data are likely to suffer from attenuation bias. Summary statistics for the variables are reported in Table E.1.

## E.2 Replication of our main results with sunshine duration data

We test the robustness of our main results by replicating the analysis in Table 2 using direct observations of sunshine duration instead of the proxy measure, cloud cover. Table E.2 reports these results, where cloud cover and other Copernicus-derived weather variables are replaced with their corresponding measures from the in-situ weather station dataset.

In the cross-sectional specification, the marginal effects are not statistically significant. However, once we account for unit fixed effects, the signs and significance of the effects closely mirror our main findings. In particular, the pooled marginal effect in column (5) of Table E.2 suggests that a one-standard-deviation increase in average sunshine duration during the 11:00 AM to 6:00 PM period over the four days preceding the sale is associated with a 0.38% increase in home prices. For the median-priced home in this sample, this translates to approximately $1,782.

## E.3 Assessing the validity of cloud cover as a proxy for sunshine duration

We evaluate the extent of measurement error introduced by potential non-linearity between sunshine duration and cloud cover—two related but distinct proxies for solar exposure. This exercise tests the validity of using satellite-based cloud cover as a linear proxy for sunshine in our main analysis.

To begin, we use weather station data to plot the relationship between sunshine duration and observed cloud cover at the daily level (Figure E.1A). While intra-day observations (11:00–18:00 CET) provide more precise temporal alignment with open house timing, daily aggregates better mirror the satellite-based cloud cover used in our main analysis. The resulting scatter plot reveals a near-linear inverse relationship. Slight deviations, particularly during the spring, suggest that allowing for non-linearity may offer marginal improvements in model fit—but the overall pattern is consistent with a linear approximation. A similar exercise using satellite cloud cover as the predictor (Figure E.1B) confirms this linearity even more clearly.

To more rigorously assess the linearity assumption, we conduct a two-stage predictive exercise. In the first stage, we predict sunshine duration from satellite cloud cover (and

Table E.1: Summary statistics, sample with sunshine duration

| N = 30,068 | Mean | SD | 25th pct. | Median | 75th pct. |
|---|---|---|---|---|---|
| **Home sales** | | | | | |
| Sale price (in 1,000 USD) | 468.75 | 229.69 | 314.80 | 391.89 | 556.01 |
| Size (sqm.) | 80.35 | 43.37 | 52.00 | 68.00 | 95.00 |
| Age (years) | 55.28 | 36.18 | 29.00 | 53.00 | 74.00 |
| TOM (days) | 10.51 | 3.23 | 8.00 | 10.00 | 11.00 |
| Lot size (sqm.) | 2,581.21 | 13,789.12 | 337.75 | 665.50 | 1,066.00 |
| Apartments (share) | 0.81 | | | | |
| Non-co-ops (share) | 0.56 | | | | |
| Mortgage rate | 2.30 | 0.39 | 1.80 | 2.41 | 2.53 |
| **Across seasons** | | | | | |
| Sunshine duration (minutes, MA) | 30.60 | 15.94 | 19.06 | 30.78 | 42.81 |
| Precipitation (mm, MA) | 1.11 | 0.20 | 1.00 | 1.02 | 1.14 |
| Sunshine duration (minutes, DOS) | 30.71 | 22.84 | 4.88 | 30.88 | 53.13 |
| Precipitation (mm, DOS) | 1.11 | 0.35 | 1.00 | 1.00 | 1.02 |
| Hours of night | 10.17 | 3.55 | 7.04 | 9.83 | 12.72 |
| **Spring** | | | | | |
| Sunshine duration (minutes, MA) | 33.80 | 14.99 | 22.62 | 34.16 | 44.47 |
| Precipitation (mm, MA) | 1.07 | 0.13 | 1.00 | 1.01 | 1.09 |
| Sunshine duration (minutes, DOS) | 34.70 | 22.76 | 10.88 | 38.88 | 57.75 |
| Precipitation (mm, DOS) | 1.07 | 0.25 | 1.00 | 1.00 | 1.01 |
| Hours of night | 9.42 | 2.43 | 7.21 | 9.10 | 11.71 |
| **Summer** | | | | | |
| Sunshine duration (minutes, MA) | 35.17 | 13.30 | 26.50 | 34.28 | 44.53 |
| Precipitation (mm, MA) | 1.13 | 0.22 | 1.00 | 1.04 | 1.18 |
| Sunshine duration (minutes, DOS) | 36.56 | 20.96 | 18.37 | 39.50 | 57.50 |
| Precipitation (mm, DOS) | 1.09 | 0.36 | 1.00 | 1.00 | 1.02 |
| Hours of night | 7.11 | 1.74 | 5.43 | 6.22 | 8.83 |
| **Fall** | | | | | |
| Sunshine duration (minutes, MA) | 22.72 | 16.35 | 8.34 | 21.56 | 33.25 |
| Precipitation (mm, MA) | 1.13 | 0.22 | 1.00 | 1.02 | 1.15 |
| Sunshine duration (minutes, DOS) | 20.70 | 21.33 | 1.00 | 12.75 | 39.50 |
| Precipitation (mm, DOS) | 1.18 | 0.42 | 1.00 | 1.00 | 1.09 |
| Hours of night | 13.94 | 2.28 | 11.94 | 14.00 | 15.85 |

**Notes:** The table presents summary statistics for the main variables in the sample using alternative weather data sourced from MET Norway (in-situ weather station data). For each observation, weather is measured at the nearest weather station within a 20 km radius, except for the Tryvann station in Oslo, where the maximum distance is restricted to 2 km due to its high elevation. Sale prices are deflated to 2015 levels using the consumer price index (CPI) and converted to USD using the exchange rate on January 2, 2023 (NOK/USD = 9.8413). *Size* refers to the interior living area. *TOM* (time-on-market) is defined as the number of days between listing and sale. *MA* denotes the moving average of weather variables over the four days preceding the sale, while *DOS* refers to the value on the day of sale. Lot size statistics are reported only for non-apartment units.

vice versa) using both linear and quadratic models that include interactions with monthly fixed effects. These models are trained on daily zip code-level aggregates. In the second stage, we estimate two variants of model (1), replacing the original variable of interest

Table E.2: Effects of sunshine duration on log of home prices

| | Cross-section | | | | Repeat sales | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Marginal effects at the means, pooled and by season | | | | | | |
| Pooled | 0.0028 | 0.0001 | 0.0015 | 0.0017 | 0.0073** | 0.0069** |
| | (0.0025) | (0.0017) | (0.0017) | (0.0017) | (0.0034) | (0.0030) |
| Spring | 0.0030 | 0.0001 | 0.0016 | 0.0019 | 0.0079** | 0.0075** |
| | (0.0028) | (0.0018) | (0.0018) | (0.0018) | (0.0036) | (0.0032) |
| Summer | 0.0053 | 0.0008 | 0.0014 | 0.0019 | 0.0073 | 0.0079* |
| | (0.0040) | (0.0026) | (0.0026) | (0.0026) | (0.0055) | (0.0047) |
| Fall | 0.0002 | -0.0006 | 0.0014 | 0.0013 | 0.0068*** | 0.0051** |
| | (0.0020) | (0.0013) | (0.0014) | (0.0014) | (0.0024) | (0.0024) |
| N | 28,351 | 28,351 | 28,350 | 28,350 | 4,716 | 4,267 |
| Adj. R. sq. | 0.7205 | 0.8768 | 0.8783 | 0.8788 | 0.9595 | 0.9639 |
| Fixed effects | MY & MQ | MY & MQ | MYQ | MYQ & MDW | YQ | YQ |
| Zip code FE | | ✓ | ✓ | ✓ | | |
| Unit FE | | | | | ✓ | ✓ |
| Holding time (weeks) | | | | | | ≥52 |

**Notes:** The table reports results from regressions of the log of home prices on sunshine duration and additional controls, using weather data from the Frost API provided by MET Norway. Weather variables are calculated as the moving averages over the four days prior to the sale. *HoN* denotes hours of night. Fixed effects are abbreviated as follows: M = municipality, Y = year, Q = quarter, and DW = day-of-the-week; hence, MYQ refers to municipality-by-year-by-quarter fixed effects. All regressions include weather controls for temperature and wind speed, along with their seasonal monthly averages. Additional controls include age of the housing unit and the mortgage rate. Cross-sectional regressions also control for property characteristics: size (square meters); an indicator for whether the unit is an apartment; the interaction between size and the apartment indicator; an indicator for non-cooperative housing units; and the interaction between lot size and a non-apartment indicator. Standard errors are clustered by three-digit zip code-by-year and are reported in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

with its predicted counterpart—i.e., using predicted sunshine duration in place of cloud cover, or predicted cloud cover in place of sunshine duration. For both cases, we compute four-day moving averages and monthly averages from the predicted values to mirror the structure of our main analysis.

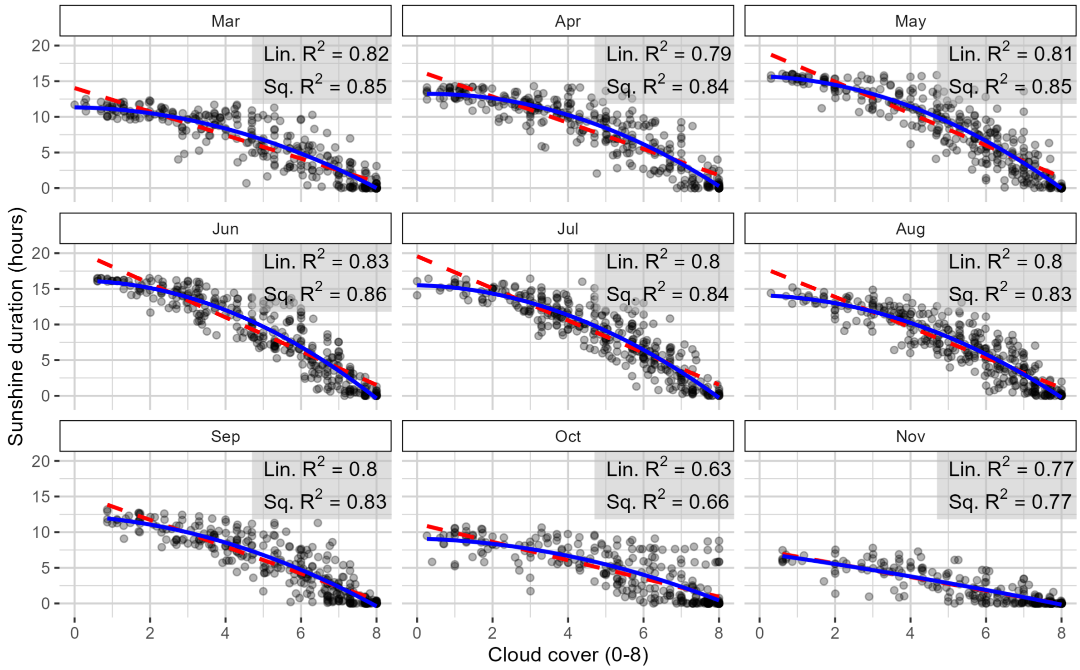
This procedure allows us to assess two key relationships: (1) whether sunshine duration, when predicted from satellite cloud cover, yields similar effects on home prices, and (2) whether cloud cover, when predicted from sunshine duration, still recovers our main results—despite the reduced sample coverage and data quality of sunshine measurements.

The results are presented in Table E.3, with corresponding model performance metrics shown in Table E.4. Columns (1)–(4) use predictions of sunshine duration, and columns (5)–(8) use predictions of satellite cloud cover. Odd-numbered columns use linear models; even-numbered columns allow for quadratic terms.

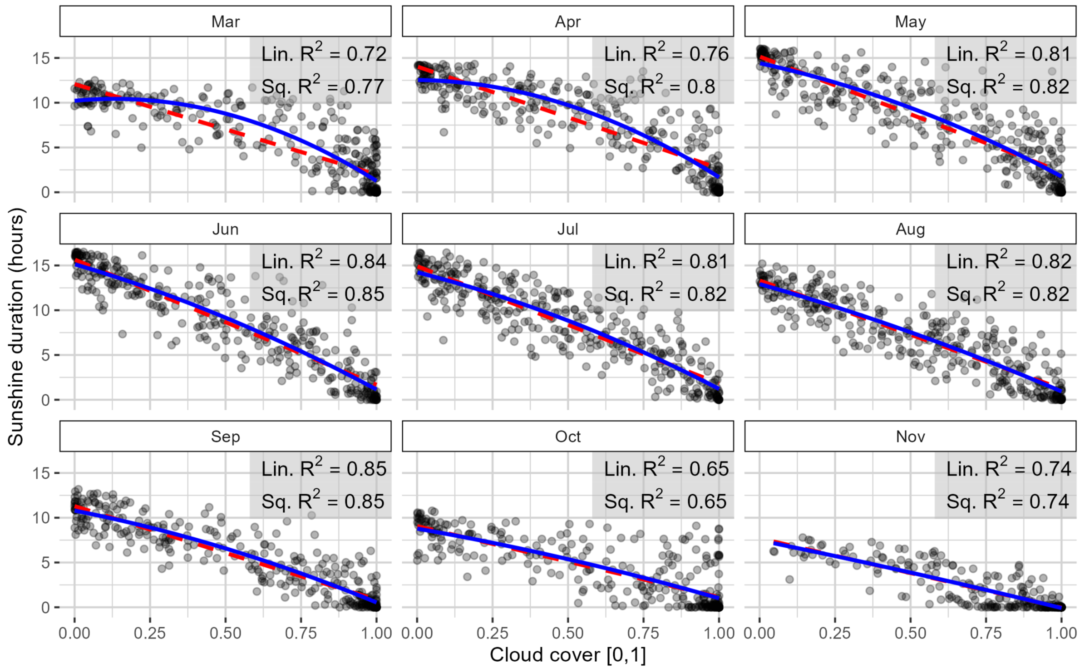
The findings are consistent and informative. In the unit fixed effects specification, the marginal effects derived from predicted sunshine (columns (3)–(4)) closely resemble those found in Table E.2. Similarly, results based on predicted cloud cover (columns (7)–(8)) align with our main estimates in Table 2. The pooled marginal effects remain stable, and the inclusion of quadratic terms does not materially change the conclusions. As expected, results from models using sunshine-based predictions (columns (5)–(8)) are slightly attenuated, reflecting the lower precision and coverage of the sunshine data.

Overall, this analysis supports the validity of our approach. The close correspondence between sunshine and cloud cover—both graphically and in predictive performance—suggests that treating satellite-based cloud cover as a linear proxy for sunshine duration is a reasonable and robust assumption.

Figure E.1: Sunshine duration versus cloud cover




(A) Sunshine duration (in-situ) vs. cloud cover (in-situ)




(B) Sunshine duration (in-situ) vs. cloud cover (satellite)

**Notes:** The figure displays the relationship between daily aggregated sunshine duration and cloud cover, segmented by month, using data from 2013 to 2023 and restricted to zip codes included in the main sample. Panel A shows sunshine duration plotted against *in-situ* (weather station) cloud cover observations, while Panel B plots sunshine duration against satellite-derived cloud cover. Each panel includes a red curve representing the fitted values from a linear regression of sunshine duration on cloud cover. The blue curve represents a regression model that additionally includes the squared term of cloud cover. $R^2$ values are reported for both the linear and quadratic specifications.

Table E.3: Effects of predicted sunshine duration and cloud cover on log of home prices

| | Pred. sunshine duration (hours) | | | | Pred. cloud cover | | | |
|---|---|---|---|---|---|---|---|---|
| Pred. model: | Lin. (1) | Sq. (2) | Lin. (3) | Sq. (4) | Lin. (5) | Sq. (6) | Lin. (7) | Sq. (8) |
| Marginal effects at the means, pooled and by season | | | | | | | | |
| Pooled | 0.0066$^{***}$ | 0.0062$^{***}$ | 0.0069$^{**}$ | 0.0067$^{**}$ | -0.0132 | -0.0138$^{*}$ | -0.0243$^{*}$ | -0.0230$^{*}$ |
| | (0.0023) | (0.0022) | (0.0033) | (0.0032) | (0.0083) | (0.0083) | (0.0127) | (0.0127) |
| Spring | 0.0068$^{***}$ | 0.0063$^{***}$ | 0.0071$^{**}$ | 0.0068$^{**}$ | -0.0152$^{*}$ | -0.0155$^{*}$ | -0.0269$^{**}$ | -0.0257$^{**}$ |
| | (0.0024) | (0.0024) | (0.0035) | (0.0034) | (0.0081) | (0.0080) | (0.0123) | (0.0121) |
| Summer | 0.0072$^{**}$ | 0.0063$^{*}$ | 0.0033 | 0.0029 | -0.0361$^{***}$ | -0.0360$^{***}$ | -0.0153 | -0.0154 |
| | (0.0035) | (0.0033) | (0.0048) | (0.0046) | (0.0121) | (0.0120) | (0.0155) | (0.0153) |
| Fall | 0.0059$^{**}$ | 0.0060$^{**}$ | 0.0105$^{***}$ | 0.0105$^{***}$ | 0.0124 | 0.0110 | -0.0308$^{*}$ | -0.0280 |
| | (0.0026) | (0.0026) | (0.0035) | (0.0034) | (0.0110) | (0.0110) | (0.0172) | (0.0172) |
| N | 52,906 | 52,906 | 12,170 | 12,170 | 37,270 | 37,270 | 9,156 | 9,156 |
| Adj. R. sq. | 0.8729 | 0.8729 | 0.9593 | 0.9593 | 0.8815 | 0.8815 | 0.9559 | 0.9559 |
| Rep. col. Table 2 | (3) | (3) | (5) | (5) | (3) | (3) | (5) | (5) |
| Fixed effects | MYQ | MYQ | YQ | YQ | MYQ | MYQ | YQ | YQ |
| Zip code FE | ✓ | ✓ | | | ✓ | ✓ | | |
| Unit FE | | | ✓ | ✓ | | | ✓ | ✓ |

**Notes:** The table presents results from regressions of the log of home prices on predicted sunshine duration (columns (1)–(4)) and predicted cloud cover (columns (5)–(8)). Columns (1), (2), (5), and (6) replicate the cross-sectional specification from column (3) of Table 2, while columns (3), (4), (7), and (8) replicate the unit fixed effects specification from column (5) of Table 2. Predictions are generated using either a linear (Lin.) or squared (Sq.) model. The linear prediction model takes the form: $Sun_t = \beta_0 + \beta_1 CC_t + \boldsymbol{\mu}_t + \beta_{\boldsymbol{\mu}}(CC_t \times \boldsymbol{\mu}_t) + \varepsilon_t$, where $Sun_t$ is the observed sunshine duration from weather stations, $CC_t$ is satellite-based cloud cover, and $\boldsymbol{\mu}_t$ denotes monthly dummies (March–November). The squared specification includes $CC_t^2$ and its interactions with monthly dummies. Prediction models are estimated using daily averages of each variable across zip codes. Weather variables are defined as four-day moving averages prior to the sale. *HoN* denotes hours of night. Fixed effects are abbreviated as follows: M (municipality), Y (year), Q (quarter), and DW (day-of-week), with *MYQ* denoting municipality-by-year-by-quarter fixed effects. All regressions include controls for maximum temperature, wind speed, and their seasonal monthly averages, as well as age and mortgage rate. Cross-sectional regressions control for housing characteristics: size, an apartment indicator, their interaction, a non-co-op indicator, and an interaction between lot size and a non-apartment indicator. Standard errors are clustered by three-digit zip code-by-year and reported in parentheses. $^{*}$ p<0.1, $^{**}$ p<0.05, $^{***}$ p<0.01.

Table E.4: Performance of prediction models for sunshine and cloud cover

| | Predicted sunshine duration | | Predicted cloud cover | |
|---|---|---|---|---|
| Pred. model: | Lin. | Sq. | Lin. | Sq. |
| Fit N | 2,938 | 2,938 | 2,938 | 2,938 |
| Fit $R^2$ | 0.831 | 0.843 | 0.792 | 0.799 |
| Fit adj. $R^2$ | 0.830 | 0.842 | 0.790 | 0.797 |
| Pred. $R^2$ | | | 0.752 | 0.761 |
| Pred. RMSE | | | 0.188 | 0.185 |

**Notes:** The table reports performance statistics from models that predict (satellite) cloud cover using sunshine duration, and vice versa. Models are estimated using a sample of daily averages across zip codes, and predictions are generated for a panel of zip code-by-day observations. Reported metrics—$R^2$ and root mean square error (RMSE)—compare predicted and observed values of satellite cloud cover at the zip code-by-day level.

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