Intra-week price patterns in the housing market*

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Abstract

This article demonstrates the existence of city-specific intra-week price patterns in the Norwegian housing market. I use a data set with exact sell dates to show that sell prices are higher on certain days. Using ask prices and observations on repeat sales in fixed effect models, I seek to control for composition effects and unobserved heterogeneity. The intra-week price patterns are shown to be associated with patterns in public-showing-day frequencies. I argue that the findings are consistent with optimizing agents acting on new information.

Keywords: house auctions, public showing day, repeat sales, sell-ask spread

JEL Codes: C21, D12, R31

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I Introduction

In Norway, houses and apartments are sold at ascending-bid auctions that often commence the day after a public showing. For some time, observers have noted that house prices tend to display intra-week patterns. In this article, I ask if house prices do indeed vary within the week, and if so, what generates this pattern.

I demonstrate that such price patterns exist, that they are different in different cities, that they are linked to patterns in public showings, and argue that they are consistent with search theory and behavior of optimizing agents. To document that there are intra-week price patterns, I rule out effects from time-invariant and time-variant features of the transacted units. To do so, I study a repeat-sales data set in which a given unit has been sold several times and on different weekdays. Using unit fixed-effect regressions, I control for time-invariant attributes such as house type, lot size, vintage, and permanent features of the neighborhood and thus rule out the possibility that the pattern is driven by a composition effect whereby certain types of houses are transacted on certain days. To control for time-variant attributes, I access the ask price for each transaction and use repeated observations of the difference between the sell price and the ask price as a fraction of the ask price, i.e., the sell-ask spread. Additionally, I examine repeated observations of the spread between the sell price and the appraisal value and the spread between the sell price and the predicted price from a hedonic model. I find a clear intra-week pattern in these spreads. In Oslo, sell-ask spreads on Mondays tend to be about two percentage points higher than spreads on Thursdays or Fridays.

To rationalize the documented patterns in spreads, I suggest that they may be interpreted within a simple search framework in which a typical public showing day (i.e., an open-house day) synchronizes the day on which information reaches the searching agents (Coles and Smith (1998)). This synchronization in turn synchronizes the timing of first bids and auction commencement. Auctions separate into different kinds depending on how many high-quality matches were made between the preferences of the viewers and the attributes of the units.

The number of matches determines the dynamics in the auction, its commencement and completion, and the selling price (Anundsen and Røed Larsen (2018) and Coles and Muthoo (1998)). The implication is that there is, for a given city, an association between a typical showing day and the day with higher prices. This association has the testable implication that when cities have different intra-week patterns in public showing frequencies they also should have different patterns in intra-week prices. They do.

The contribution of the article is purely empirical and consists of combining different data sets to document and explain price patterns in the housing market. To link spread patterns to showing patterns, I complement transaction data with the acquisition of data about public showing days in different cities. I also acquire realtors' bid logs from auctions in different cities. These logs allow me to validate the results on prices and showings by studying the bid activity patterns.

My findings have several implications. The knowledge of an intra-week house price regularity and the temporal proximity between showings and subsequent market activity might help moving households, realtors, and regulators to improve their planning of actions and understanding of outcomes. Moreover, I show that a non-obvious price pattern can be explained by a plausible generating mechanism, which is consistent with optimizing behavior. This explanation contributes to the debate on efficient markets.

The next section contains a literature review, an outline of the theoretical framework used, and an explanation of how I intend to use fixed-effect models. In the subsequent section, I describe my data and present a brief institutional background. Section four contains a description of regularities. Section five contains a presentation of this article's main empirical findings on the existence of intra-week price patterns. Section six contains evidence supporting the hypothesis that a pattern in public showing day is the generating mechanism of a pattern in prices. In the subsequent section, I examine the role played by time-on-market and discuss challenges from systematic errors in ask prices or from strategies when ask prices are set. I perform robustness controls using predicted prices from a hedonic model and appraisal values from external appraisers. The last section contains concluding remarks and suggestions for future research.

II Literature and empirical framework

Literature

The research literature covers weekday effects in markets, price anomalies in auctions, and search and matching mechanisms. Research on weekday effects has documented that such effects do occur in many types of markets. Wong et al. (1999) find a weekday effect on the Shanghai Stock Exchange. Cho et al. (2007) detect a Monday effect in stock returns. Pettengill (2003) reports weekday effects in futures, treasuries, and currencies. Foros and Steen (2013) find weekly price cycles in Norwegian gasoline prices. Doyle and Chen (2009) document that a weekday effect appears to exist in many markets.

In the price-anomaly strand of the literature, McAfee and Vincent (1993) focus attention on the declining-price anomaly, a phenomenon that arises when two similar objects are sold immediately after one another and the second object sold is sold at a lower price. McAfee and Vincent study wines and find that even though identical wines are sold only minutes apart, the earlier sales obtain higher prices, a pattern termed "the afternoon effect" by wine traders. This effect had been analyzed in Ashenfelter's (1989) study on wine auctions and it has been found in art auctions (Beggs and Graddy (1997)) and in Dutch auctions (van den Berg et al. (2001)). In the real estate market, Ashenfelter and Genesove (1992) study an auction of 83 condominium units held in Princeton, New Jersey in April 1990 and resold later. They find convincing evidence suggesting that early buyers pay a premium and state that "these empirical results should surprise most economists" since they suggest the possibility of a "winner's curse," given that most condominiums were bought by investors planning to resell.

This article, however, builds on the search literature. When a unit is publicly shown and the showing is on a given day, buyers are informed about their own match utility on that day. Some housing units achieve multiple high matches; other units achieve fewer matches, one match, or none. One hypothesis is that units matched with multiple buyers have a higher probability of receiving earlier bids and more bids since more bidders and more eager bidders participate (Stevenson and Young (2015) and Anundsen and Røed Larsen (2018)). These units might have a higher probability of being sold faster and at higher prices.

Variations of such ideas can be found in several search studies (Diaz and Jerez (2013), Genesove and Han (2012), Kashiwagi (2014), and Maury and Tripier (2014)). The models in Coles and Muthoo (1998) and Coles and Smith (1998) are especially useful. Coles and Smith study trading in a marketplace and model how a buyer first examines his matches with the existing stock then, subsequently, examines the inflow of goods. Coles and Muthoo model how traders separate into either a procedure of strategic bilateral bargaining or a process of bidding, depending on the number of participants. These two search models serve as an interpretative framework for this article in that I use both the importance of the inflow of goods and the separation into different procedures. First, I use the inflow idea when I suggest that the public showing represents an inflow of new information on new units and the day of showing represents a particular timing of this information inflow. The relevant information about units for sale first becomes fully available when units are shown in the public showing (i.e., the open house). Even if prospective buyers can use advertisement information to guess about a unit's suitability before the public showing, the quality of the match between their own preferences and the unit's attributes is first fully revealed upon physical inspection. When many units are shown the same day, the timing represents a pattern of information inflow that affects the subsequent timing of the stream of bids. This is similar in spirit to Coles and Smith, who write, "... the flow of new entrants should be an important explanatory variable for the aggregate trading rates."

Second, I use the notion of different processes by suggesting that auctions separate into different kinds depending on the number of interested bidders. A typical showing day within a market represents a synchronization of when bidding might commence. However, the probability that bidding commences soon after the public showing is affected by the number of interested bidders. On the public showing day, it becomes clear that some units are well-matched with multiple buyers whereas other units are matched with only a few buyers, one, or none. The well-matched units might sell during auctions characterized by an early start, having many bids, and having a higher probability of high bids. The implication is that there would be an inverse relationship between the number of days after the showing and the size of the sell-ask spread. The closer the sale is to the showing day, the higher the sell-ask spread would tend to be. This idea resembles the idea in Coles and Smith, who state: "By directing search efforts to a common arena, marketplaces speed up the rate at which traders find each other." Broadly interpreted, a "common arena" might not be only a space shared by many, but also a point in time shared by many. In this article, the basic idea is that the public showing day is a potential accelerator for matching buyers with sellers and that this accelerator affects the temporal pattern of sell-ask spreads.

Empirical framework

This article follows individual units over time to control for time-invariant unit-specific features and uses sell-ask spreads, that is, the difference between the sell price and the ask price as a fraction of the ask price, to control for time-variant factors. The ask price reflects information from the most knowledgeable source, the seller. However, since a seller might employ strategic pricing, be financially stressed, or be otherwise biased in setting the ask price, I also use, in robustness checks, model-predicted prices and appraisal values in computing spreads.

I begin by using the simplest approach. I first choose to use as a temporal marker a typical public showing day, Sunday, and define an early (E) and a late (L) sale, respectively, as a sale early in the week (Monday or Tuesday) or late in the week (Thursday or Friday). For each unit sold, I compute a sell-ask spread. I define four segments, exhausting all combinations of the timing of the two sales: Segment (E,E) consists of units that have been sold early twice.

Segments (E,L), (L,E), and (L,L) consist of units that have been sold early and late, late and early, and late twice in the two sales. For each unit, I compute the spread difference, that is the first sell-ask spread less the second. For each segment, I compute the mean spread difference across units.

There are several challenges to this simple approach. First, since sale dates are not assigned randomly, units in the early-late (i.e., E,L) segment might be drawn from a different distribution than the units in the late-early segment. I examine this possibility below through checks for balance. Second, since it is fathomable that the probability of a unit's belonging to a given segment is a function of time, I also use a unit and time fixed-effect model. This set-up also controls for the possibility that strategies in ask prices and auction intensities contain cycle dependencies. Robustness checks involving appraisal values and model predictions would uncover cycle effects in ask prices.

The fixed-effect model is specified as a regression of the sell-ask spread for unit i in sale j = 1,2, $S_{i,j}$, on a fixed effect for unit i, θ_i, a dummy for an early sale, $E_{i,j}$, and a collection of dummies for the time period of the sale, $D_{i,j}$:

$$S_{i,j} = \theta_i + vE_{i,j} + dD_{i,j} + e_{i,j}, \tag{1}$$

in which $e_{i,j}$ is an error term assumed to be zero mean. I use time fixed effects to control for the cycle. Unit i is sold two times at $(t_{i,1}, t_{i,2})$ and unit k is sold at two different times $(t_{k,1}, t_{k,2})$. These two time pairs might differ in length of time apart and in position. To control for the sale date using time fixed effects, I use a collection of vectors of dummy variables, D, consisting of year and month dummies.[1]

The model specified above is sensitive to the assumption of identical effects across geographical regions. Since there are institutional differences between cities regarding typical

[1]One could use both a first difference (FD) and fixed effect (FE) set-up. FE makes it convenient to control for time fixed effects since each transaction date corresponds to an entry in a time dummy.

public showing days, I estimate models for each city and for a pooled sample, using interaction terms between cities and a dummy for the day (and two first days) after the typical public showing day. These set-ups allow me to test the hypothesis that a different intra-week pattern of public showing is associated with a different intra-week pattern of sell-ask spreads.

III Data and institutional background

Transaction data

The data are sourced from the firm Eiendomsverdi, which is a privately owned firm specializing in acquiring and combining data from real estate agencies, public registry, and on-line advertisements with other sources such as geographical information. The data set covers the period from 1 January 2002 to 1 February 2014 and is similar in coverage to the data set used by Anundsen and Røed Larsen (2018). The data comprise transactions that are advertised on-line and in which a realtor has been a mediator. The data include information on both transactions and units, for example, the date when the advertisement was registered on-line, the date of the accepted bid, the sell price, the ask price, common debt, unit identification, map coordinates, and hedonic attributes such as size, number of rooms, number of bedrooms, floor number (of an apartment unit), etc. Ask price is the last ask price before an agreement of sale has been made, which is relayed to Eiendomsverdi by realtors. Sample controls undertaken by Eiendomsverdi show that few ask prices in the period were revised and that the practice of revising ask prices affects mostly transactions involving units with a long time-on-market (TOM).

Data trimming was first performed by removing observations lacking an exact sell date and other variables. I truncated on the 0.1 and 99.9 percentiles on sell price, size, square-meter price, and sell-ask spread. I kept only owner-occupier units. I used a standard hedonic model[2] to predict prices (Rosen (1974)) in order to control for possible systematic biases in

[2]Sell price regressed on log(size), squared(log(size)), type dummies, construction year, interaction vari-

the ask price. In Table 2, the ratios of ask price on predicted price in the rightmost column of Table 2 demonstrate that ask prices and predicted prices capture similar features of the unit.

I used the predicted prices from the hedonic model to trim the data in order to remove dubious entries, typing errors, and non-market transactions. I truncated on the sell price to predicted price ratio, at ratios 0.4 and 2.66 (1st percentile and 99th percentile). The resulting data set contains 472,503 observations. Table 1 summarizes the key variables.

Table 1. Data summary

	Percentiles and mean					
No. of obs.	472,503					
	10th	**25th**	**Median**	**Mean**	**75th**	**90th**
Unit size (sq. m.)	56	77	114	121.1	155	196
Sell price (NOK)	1,190,000	1,550,000	2,100,000	2,451,029	2,977,018	4,100,000
Sell-ask spread (%)	-6.8	-3.1	0.0	1.9	5.7	12.8

The data on repeat sales

I identified 353,969 unique unit identifiers, of which 73,114 units were sold exactly twice and on separate dates, constituting 146,228 transactions.

The data on showing day frequencies

Since showing day/date is not included in the transaction data, Eiendomsverdi accessed from a sample of realtors data from 2013–2017 on public showing days. The data set includes 91,321 observations of both owner-occupied units and co-ops from a national database. The data are not a complete list of showings, but a sample from selected, participating realtors. The capital Oslo is oversampled. However, the realtors follow common public-showing-day

ables for apartment/size and Oslo/size. City/region and month fixed effects. Adj. R2: 0.661.

practices in the cities where they work. Table A2 tabulates showing frequencies for six Norwegian cities.

The data on bidding frequencies

Through Eiendomsverdi, I accessed data from February 2011 to December 2016 on dates of registered bids from one collaborating realtor's bid log. This realtor has a substantial presence in Oslo, which the data reflect, and the data do not contain observations on all cities. The data set includes 129,610 observations of registered bids. I selected units with descriptions that include the Norwegian phrases for "detached," "semi-detached," "row house," and "apartment" in order to exclude bids on lots, commercial real estate, etc. The trimmed data consist of 49,117 registered bids. I use the date on which a bid is received by the realtor. The frequencies of received bid dates across weekdays are tabulated in Table A3.

Institutional background

In Norway, most transactions involve an on-line advertisement, a public showing, and a subsequent process involving prospective buyers. Typically, a house is announced for sale some time before a showing, which in Oslo typically is held on Sunday or Monday. Announcements are typically posted on the nationwide on-line service Finn.no and, especially early in the data-coverage period, in newspapers. The auction commences after the last showing, but some units are sold soon after advertisement and before the auction, based on bilateral communication between seller and bidder. The auction is an ascending-bid auction in which communication with the realtor takes place through electronic communication devices (e.g., a telephone, short-message-system texts, e-mails, or other digital solutions). The realtor informs participants of developments in the auction using continuous updates. Both bids and acceptances are legally binding. Expiration bids are legal, as are conditional bids (e.g., conditioned on funding). The market for owner-occupier units is large since about four of five Norwegians are owner-occupiers, depending on the unit of analysis (households, individuals, addresses).

For my purposes here, I find it useful to differentiate between "transaction process," which refers to any length of time between the date of the advertisement and the date of the transaction, and "auction," which means an activity occurring during a short period of time in which several bidders make competing bids. A proportion of units sell after a long period on the market, and these units might have been sold without contested bidding rounds. In fact, many of these units are sold after a one-on-one negotiation between the seller and a single buyer (Chow et al. (2015) and Rosato (2017)). However, some units with a long TOM might have been offered at auctions two or three times, and such auctions might or might not have started on a specific weekday. Most likely, the second round of showing day(s) occurs on the same weekday(s) as the first round of showing day(s)does. In the negotiation case, the transaction process should not be termed an auction. In the renewed auction case, these renewed attempts are best conceptualized as completely new transaction processes. Re-classification, however, is impossible given the information contained in the *transaction* data set, since this data set contains no information about the showing day(s).

IV Observable regularities

Table 2 tabulates average sell prices across the week and a pattern is easily detectable. We see that over the period from 1 January 2002 to 1 February 2014, the average sell prices for bids accepted on a Monday or a Tuesday were NOK 2,531,201 and NOK 2,574,379, respectively, while they were NOK 2,352,642 and NOK 2,278,319, respectively, for bids accepted on a Thursday or a Friday. This tabulation shows that sell prices tend to be higher early in the week.

Table 2. Sell prices and ask prices across weekdays. Norway, 2002–2014

		Averages			
Weekday	*No. obs.*	*Sell*	*Ask*	Spread (st.dev.)	Ask/Predicted
Monday	106,191	2,531,201	2,461,696	0.0306 (0.0897)	0.999
Tuesday	106,331	2,574,379	2,521,314	0.0231 (0.0857)	1.006
Wednesday	96,214	2,444,626	2,410,424	0.0184 (0.0863)	1.004
Thursday	79,048	2,352,642	2,336,481	0.0125 (0.0857)	1.009
Friday	76,287	2,278,319	2,276,434	0.0069 (0.0842)	1.016
Saturday	5,222	2,409,531	2,424,434	-0.0010 (0.0746)	1.050
Sunday	3,210	2,499,681	2,490,642	0.0102 (0.0818)	1.047
TOTAL	472,503	2,451,029	2,413,598	0.0191 (0.0868)	1.007

Table 2 also tabulates transaction volumes (no. obs.) and ask prices across the week. We observe that transaction volumes and average ask prices are higher on Mondays and Tuesdays than on Thursdays and Fridays. The ask-price regularity is less pronounced than the sell-price pattern, indicating that a quality composition effect might partly, but not fully, explain the weekday effect in sell prices. The second rightmost column presents weekday averages and standard deviations of sell-ask spreads. Again we observe an intra-week regularity as the spread decreases from Monday to Saturday. Differences in spread are large and statistically significant. [3] The rightmost column presents the mean ask-predicted ratio. The ratios lie around unity. The exception is week-end transactions, but since transaction volumes are low, we are cautious to interpret the ratios.

V Empirical results

The composition effect

Units sold earlier in the week might have different characteristics and might be sold in different markets than units sold later in the week. Table 3 tabulates characteristics for units sold on Mondays and Tuesdays versus units sold on Thursdays and Fridays. To illustrate possible time

[3] For example, $z = (spread_{Tu} - spread_{We})/(s^2_{Tu}/n_{Tu} + s^2_{We}/n_{We})^{0.5}$. Since $z = 12.3$, we can reject the null of no difference.

effects, I present the statistics both for the whole period and for one randomly selected month, May 2006. I extract and study this random month to examine the degree of variation across years and months.

We observe that the segments are not balanced, since unit characteristics and transaction covariates are substantially different. Units sold early in the week are more likely to be smaller apartments located in Oslo than are units sold later in the week. Among the units sold early in the week in May 2006, 23.1 percent were Oslo sales compared to 12.5 percent for units sold late in the week. This difference indicates that Monday-Tuesday sales do not occur randomly. Instead, sales early in the week are the result of a selection process, for which I below offer a hypothesis involving a city-specific effect that in turn relies on the day of the public showing. We observe a substantial difference in the sell-ask spread for the full period 2002-2014 since the mean sell-ask spread is 0.028 for the Monday-Tuesday sales and 0.0097 for the Thursday-Friday sales. However, since the segments are not balanced, this difference might be caused by both a true early-sale effect and a geographical effect. Below, I deal with geographical effects by segmenting on cities in combination with unit fixed-effect models.

Table 3. Characteristics of unit attributes and transaction outcomes. Means and fractions (standard deviations). May 2006 and 2002–2014

	A random month, May 2006		The whole period, 2002–2014	
	Mon–Tue sales	Thur–Fri sales	Mon–Tue sales	Thur–Fri sales
Size, sq.m.	120.4 (55.0)	123.4 (56.8)	119.4 (55.5)	123.4 (55.3)
Oslo, fraction	0.231 (0.42)	0.125 (0.33)	0.218 (0.41)	0.098 (0.30)
Apartment, fraction	0.341 (0.47)	0.295 (0.46)	0.357 (0.48)	0.300 (0.46)
Construction year	1962 (68)	1964 (36)	1964 (65)	1966 (59)
Spread	0.0620 (0.094)	0.0388 (0.093)	0.0268 (0.088)	0.0097 (0.085)
TOM, days	30.4 (59.4)	43.0 (83.5)	38.4 (65.3)	45.2 (71.4)
No. obs.	2,194	1,045	212,522	155,335

Notes: See the next sub-section and Table 4 for a word of caution on the spread distribution. No. obs. for Mon–Tue and Thur–Fri is smaller than 472,503 since the partition into Monday–Tuesday sales and Thursday–Friday sales is not exhaustive.

The number of observations in this table is larger than the number of observations in Table 4 since Table 4 restricts the samples to conditions on two transactions.

Evidence from repeat sales

The imbalance in Table 3 informs us that it would be useful to hold the unit constant while varying which day the unit is sold. Partitioning the workweek into early (Monday and Tuesday) and late sales (Thursday and Friday) leaves four combinations of the first and second sales: (E,E), (E,L), (L,E), and (L,L). The first and the fourth combinations represent a replicated process. The second and third combinations represent different processes since units in these two groups are exposed to different sales days. This set-up allows us to ask what would happen to a unit sold early in the week were it instead sold late in the week and vice versa. I define the early-sale effect as the effect on spreads from a sale close to the public showing day and I start the analysis by using Sunday as the typical showing day.

Table 4 tabulates the mean difference between the first (in chronological order) sell-ask spread less the second sell-ask spread for the four combinations. The rightmost column shows the simulated, non-parametric 99 percent confidence intervals obtained using a Monte Carlo bootstrap technique.[4] For the units that had early sale processes both in sales 1 and 2 (E,E), we observe that the mean difference between the spread observed in the first sale and the spread observed in the second sale is close to zero, 0.00058, and zero is contained in the simulated confidence interval. For the units sold late twice (L,L) the mean difference between the spreads is small, 0.0038. This difference is statistically significantly different from zero, as we see from the computed confidence interval, but the effect is small.

The main thrust of my argument can be found in the second and third rows. These rows represent units that had different sales timings. We see that for the units that sold early first and then late (E,L), the mean difference between the two spreads is 1.6 percentage points[5]. Conversely,

[4]I employ a Monte Carlo bootstrap simulation because of potential distribution issues arising from seller behavior. Spreads have thicker right tails. To see why, keep in mind that a seller would tend to accept a very high bid, but would not necessarily accept a very low bid. Thus, the distribution of spreads is asymmetrical with a thicker right tail.

[5]Throughout this article I comment upon the spread. Keep in mind that when the spread increases by p percentage points, the increase in the sell price amounts to p percent of the ask price.

for the units that sold late first and then early (L,E), the mean difference between the two spreads is -1.1 percentage points. The reversal of the sequence explains the reversal of the sign. The absolute values indicate the estimated magnitude of the effect. Together, the two estimates form a range of the estimated effect: between 1.1 and 1.6 percent of the ask price. Keep in mind that the influence of a confounder, renovation or lack thereof (depreciation), is minimized in this set-up since ask prices do in fact tend to reflect renovation or depreciation and ask prices are incorporated in the sell-ask spread.

A possible confounder is an unobserved, latent factor that influences the estimates. For example, one could worry that E,L units had a longer (shorter) time period between transactions than did L,E units, and given that spreads might contain a time component, there could be a bias in the estimates of the effect. This particular concern, however, can be put to rest by inspecting the statistics for the holding period (i.e., "Date 2 - Date 1" in panel A). There we see that the average periods between sale one and sale two for the E,L and L,E segments are 1,517 days and 1,531 days, respectfully. This means that on average we observe comparable holding times. In fact, we do observe that the two segments with opposite sequences (the E,L and L,E segments) are highly comparable on observable characteristics such as size (the average is 116 square meters for both segments), share of transactions that are apartments (35 percent versus 38 percent), and TOM (43 days for both).

However, the check for balance uncovers a difference in the share of transactions in Oslo. The E,L segment has a share of 13 percent versus 18 percent for the L,E segment. Thus, if some institutional arrangement generates an intra-week pattern and this arrangement varies across cities, the estimated effects might be biased. I explore this possibility below when I examine whether the showing day might generate the result and might vary across cities.

Panel C reports the results from a regression of the differenced spreads across units onto four dummy variables, representing the four combinations of an effect from an early sale or not.[6] The regression results show the same pattern. The two estimators of the early-sale effect are in absolute values, 1.4 percent of the ask price (E,L) and 1.2 percent of the ask price (L,E).

[6] I can include all four combinations since they are not exhaustive when sales on Wednesday, Saturday, and Sunday are unclassified.

Below, I address issues arising from the results in Table 4. First, I must hold constant the geographical elements. I do so by segmenting on Oslo. Second, I must control for the timing of each sale within the sale pairs. I do so by using a unit and time fixed-effect regression model.

Table 4. Differencing. Means and regression. Norway, 2002-2014, 2 transactions

Panel A: Checks for balance. Means (st.dev.)				
	I	**II**	**III**	IV
1st sale	Early	**Early**	**Late**	Late
2nd sale	Early	**Late**	**Early**	Late
Size, sq.m.	110 (53)	**116 (53)**	**116 (54)**	119 (53)
Oslo, share	0.31 (0.46)	**0.13 (0.34)**	**0.18 (0.39)**	0.065 (0.25)
Apartments, share	0.44 (0.50)	**0.35 (0.48)**	**0.38 (0.49)**	0.33 (0.47)
TOM, days	36 (44)	**43 (49)**	**43 (49)**	46 (52)
Date 2 - Date 1, days	1,566 (888)	**1,516 (890)**	**1,531 (903)**	1,497 (886)

Panel B: Repeat-sale spread differences				
1st sale	**2nd sale**	**No. obs.**	**Mean (st.dev.) Spread 1 - Spread 2**	**Non-parametric 99 % Conf. Int.**
Early	Early	16,221	0.000576 (0.108)	(-0.0016,0.0028)
	Late	**9,512**	**0.0156 (0.107)**	**(0.013,0.018)**
Late	**Early**	**10,186**	**-0.0106 (0.106)**	**(-0.014,-0.0076)**
	Late	8,427	0.00383 (0.107)	(0.00093,0.0067)

Panel C: $S_{1,i} - S_{2,i} = a + bD_{E,E,i} + cD_{E,L,i} + dD_{L,E,i} + eD_{L,L,i} + u_i$				
Intercept	$D_{E,E}$	$D_{E,L}$	$D_{L,E}$	$D_{L,L}$
0.0011 (0.0006)	-0.00056 (0.0011)	0.014 (0.0013)	-0.012 (0.0012)	0.0027 (0.0013)
No. obs.	73,114			
Adj. R2	0.004			

Notes: TOM = (TO1 + TOM2)/2. In Panel B, I compute the difference between spread 1 and spread 2 for each unit, then calculate the mean and standard deviation of this difference across units. In Panels B and C, "number of observations" refers to the number of transactions observed in the data set in which I have required that there be two sales and that the two sales must have occurred on different dates. While Panel B leaves out sales on Wednesdays, Saturdays, and Sundays, Panel C includes them and this explains the difference in the number of observations. The notation $S_{1,i}$ represents the spread of unit i on transaction 1. The date of transaction 1 differs across units, but the subscript t is suppressed. "E" is short for a Monday or Tuesday sale and "L" is short for a Thursday or Friday sale. The non-parametric confidence interval is computed using a Monte Carlo bootstrap resampling technique. It draws with replacement a data set of size N from a data set of size N. It is included to handle asymmetries in the distribution of the spread differences. In Panel C, the estimated standard errors of the coefficient estimates are given in parentheses. They are White heteroskedasticity-consistent estimates computed using the vcovHC function in the "sandwich" package in R. Types HC1 and HC3 yield consistent estimates.

Controlling for geography: A unit and time fixed-effect model for Oslo

Table 4 uncovers a geographical imbalance since the Oslo share is asymmetrically distributed across the four segments. A first step to isolate the early-sale effect from a geographical effect is to segment on Oslo and run a unit and time fixed-effect regression.

Table 5 reports results from three regressions. Model I is a standard OLS regression of the sell-ask spread onto an intercept and a dummy for a sale on Monday or Tuesday. The estimated coefficient of 0.0297 indicates that a Monday-Tuesday sale is associated with a 3 percentage points higher spread. Model II is a unit fixed-effect regression with an estimated coefficient of 0.0260, indicating a 2.6 percentage points higher spread when the sale is completed on a Monday or a Tuesday. Model III is a unit and time fixed-effect regression that controls for temporal effects. Since each unit is observed two times, each spread in the sales pair of each unit is assigned dummy entries for year and month. Having controlled for cycle effects, the estimated early-sale coefficient is 0.0193.[7] The interpretation is that a sale on Monday or Tuesday is associated with a 1.9 percentage points higher spread. While the early-sale coefficient estimates are statistically significant, the explanatory power is low since the dependent variable is the sell-ask spread. The ask price contains the seller's assessment of the market value of all relevant attributes. Thus, the spread is the residual of the sell price after the ask price has been accounted for.

[7] I have run model III with interaction terms between the early-sale effect and month dummies. The main pattern is intact and only two of eleven estimated interaction coefficients were statistically significant.

Table 5. Segmented regressions of the sell-ask spread on early sales. Oslo, 2002–2014, exactly 2 transactions

	Spread regressed on		
	I	II	III
Intercept	0.0224 (0.00078)		
Early sale (E)	0.0297 (0.0010)	0.0261 (0.0014)	0.0193 (0.0013)
Time fixed effects	NO	NO	YES
Unit fixed effects	NO	YES	YES
n	13,158	13,158	13,158
T	2	2	2
N	26,316	26,316	26,316
R2	0.0310	0.0255	0.162
F-statistic (p-val.)	844 (2.2-e16)	345 (2.2e-16)	106 (2.2e-16)

Notes: White heteroskedasticity-consistent errors computed using the vcovHC function in the "sandwich" package in R (types HC1 and HC3 yield consistent estimates). "T" is the number of transactions per unit. "Early sale" is a dummy variable. It is unity if the transaction takes places on a Monday or a Tuesday; otherwise zero. Time fixed effects are captured by time dummies (11 months, 12 years). There are no intercepts reported in models II and III, because there are intercepts for each unit. I report R2, not Adj. R2, since the number of intercepts is high in the unit fixed-effect set-ups. For the FE estimation, I use the plm function in R, using the "within"-model specification. I have employed alternatives, but do not report results.

VI Showing day as a generating mechanism of the early-sale effect

Comparing the estimated effects in Tables 4 and 5, we observe that the early-sale effect is larger in Oslo than in the rest of Norway. This difference implies that there must be areas in Norway in which the effect is weaker. Following the hypothesis that the showing day generates the intra-week pattern, I look for markets with different showing days and investigate whether changes in public showing days are associated with changes in the intra-week spread pattern.

Tables A2 and A3 in the Appendix tabulate showing-day frequencies and bidding frequencies across weekdays for different Norwegian cities. Since the period covering showing data is not identical to, and is shorter than, the period covering transaction data, we must be cautious when we interpret the patterns. Given that city patterns of showing frequencies are relatively stable over time, however, they offer the possibility of testing the hypothesis that the intra-week spread differences are associated with showing days.

There are noticeable differences in showing practices. For example, while Sunday in Oslo has a 44 percent share of public showings, Wednesday has a share of 38 percent in Kristiansand. In Trondheim, Wednesday is also a popular showing day, with 41 percent. In Bergen, however, Monday, Tuesday, and Wednesday are showing days with high frequencies: 19, 27, and 25 percent, respectively. Drammen follows the Oslo pattern with 35 percent of showings on Sunday. In Stavanger, Monday has the highest frequency, 28 percent. From Table A3 we see that these differences in public-showing practices appear to spill over into differences in bidding frequencies throughout the week. While Oslo has many public showings and high bidding frequencies early in the week, Bergen has many mid-week public showings and thus has high mid-week frequencies of bidding.

I segment the repeat-sale data set with exactly 2 sales into six segments, one for each city. For each city, I run a unit and time fixed-effect regression of the sell-ask spread onto a space consisting of five workday dummies, 12 year dummies, and 11 month dummies. The results are reported in Table 6 Panel A.

The regression results are consistent with the hypothesis that an intra-week pattern in spread differences is associated with an intra-week pattern in showing-day frequencies. While results from estimating the early-sale effect for Oslo are reported in Table 5 above, Table 6 also reports Oslo effects to facilitate comparison between results based on different specifications. To study the effect on all workdays of the week, I here split the effect into five workdays. In Oslo, the dummy coefficient for Monday, the day after the day with highest share of showings, is estimated at 0.015 and is statistically significant. Thus, a Monday sale is associated with a spread 1.5 percentage points larger than that of non-workdays, and 2.4 percentage points (1.5 - (-0.9)) larger than that of a Thursday or a Friday sale. Trondheim, the third-largest city in Norway, has another public-showing-day pattern with peak showing days on Tuesdays and Wednesdays. For this city, the estimated coefficient of the Monday dummy is smaller and statistically insignificant while the estimated coefficients of the Tuesday-Thursday dummies are statistically significant and about

0.03 for all three days. By inspection, we see that there is an association between the estimated coefficients and the showing patterns in Table A3.

This pattern can be tested in one regression with pooled data from all 6 cities. In Model I, I interact a city dummy variable and a dummy variable for *the day after* that city's most frequent showing day. Thus, I construct a dummy variable defined in this way: Oslo*Monday + Bergen*Wednesday + Trondheim*Thursday + Kristiansand*Thursday + Stavanger*Tuesday + Drammen*Monday. In Model II, I interact a city dummy variable and a dummy variable for *the two days following* that city's most frequent showing day. The regression results are reported in Table 6 Panel B. Results from Model I show that, for a pool of six cities, the early-sale effect is estimated at 1.4 percent of the ask price for Model I and 1.2 percent of the ask price for Model II.

Table 6. Regressions of the sell-ask spread on workday dummies, 2 transactions, 6 cities, 2002–2014

Panel A: City-segmented regressions									
City	Peak showing	Mon	Tue	Wed	Thur	Fri	U/T FE	N	R2
Oslo	Sun-Mon	0.015**	0.006	-0.009	-0.009	-0.009	Yes	26,316	0.164
Bergen	Tue-Wed	0.021**	0.020**	0.017*	0.002	-0.001	Yes	8,908	0.196
Trondheim	Tue-Wed	0.008	0.031***	0.029***	0.028***	0.015*	Yes	6,738	0.147
Kristiansand	Wed-Thur	-0.005	-0.016	-0.005	0.007	0.012	Yes	3,432	0.211
Stavanger	Mon-Tue	0.007	0.009	0.001	-0.011	-0.017	Yes	5,754	0.110
Drammen	Sun-Mon	0.034*	0.011	0.003	-0.007	-0.019	Yes	2,630	0.128
Panel B: Pooled six-city regression									
Model I: City*(Peak showing day + 1)									
6 cities (I)				0.0136***			Yes	53,778	0.106
Model II: City*(Peak showing day + 1 and + 2)									
6 cities (II)				0.0122***			Yes	53,778	0.106

Notes: The term "Peak showing days" refers to the most frequent showing days in a data set other than the transaction data set. The showing data cover the period 2013-2017. "U/T FE" means unit and time fixed effects. Unit fixed effects are ensured by an intercept per unit in a data set with repeat sales of 2 transactions. Time fixed effects are captured by time dummies (11 months, 12 years). Mon-Fri are short notations for the coefficient of weekday dummies. "Peak showing day + 1" represents a dummy variable that is unity when the transaction occurred on the day after the peak showing day (e.g., on Monday for Oslo). For the FE estimation, I use the plm function in R, using the "within"-model specification. White heteroskedasticity-consistent errors are reported from the vcovHC function in the "sandwich" package in R. Types HC1 and HC3 yield consistent estimates. I use short notations of statistical significance: *** for t-values above 3.29, ** for t-values above 2.58, and * for t-values above 1.96. I report R2, not Adj. R2, since the number of intercepts is high in the unit fixed-effect set-ups.

VII Discussion

Controlling for TOM

The existence of an early-sale effect raises the question of what generates it. The seller cannot control the auction process; he controls only the date of the public showing and the date of his acceptance of a bid. He does not control the timing of bids nor the expiration date on bids.

One hypothesis, mentioned above, is that the timing of the public showing affects the timing of the arrival of the accepted bid. The transaction process might self-select into "fast-track," "medium-track," or "slow-track" processes, a possibility that yields testable implications. The intra-week spread pattern should be minimal for fast-track processes. The reason is that fast-track processes most typically do not involve an auction at all because the buyer bids before the public showing in a one-on-one engagement. The intra-week pattern should be maximal for medium-track processes since most of these processes involve a public showing followed by an auction shortly thereafter. For slow-track processes, the intra-week pattern should be more pronounced than the fast-track processes, but smaller than the medium-track processes. The reason is that these processes contain both auctions and one-on-one negotiations between seller and buyer. In Table A1, I find some support for these hypotheses. I partition transactions into three categories of TOM while controlling for geography by segmenting on Oslo to keep showing practice and bidding practice constant. The segments are: TOM below 7 days, between 7 and 12 days, and above 71 days (cut-offs represent the 10th, 50th, and 90th percentiles of TOM)[8].

From Panel A in Table A1, I make the two observations: i) spreads are generally higher for the segment with a shorter TOM and ii) spreads are of similar magnitude within segments of TOM.

[8]There are 1,773 observations of TOM exactly equal to 7 days. Thus, the number of observations below the cut-off is not exactly ten percent of the total.

We find that for fast-track processes, there is little evidence of any early-sale effect. For example, the mean spread on Mondays is 0.088 while it is 0.094 on Fridays. However, the evidence is mixed. For slow-track processes, I do detect an intra-week pattern since the Friday spread of -0.024 is noticeably smaller than the Monday spread of -0.004. For medium-track processes, I also detect an intra-week pattern since the Monday spread of 0.085 is the largest of the workweek-day spreads. However, the Friday spread is large.

In Panel B, I follow repeat sales of the same unit to run unit fixed-effect regressions. I segment on Oslo transactions of twice-sold units using the same conditions for both the first and second sales. Then I use a unit fixed-effect regression by regressing sell-ask spreads onto a dummy variable for an early sale (Monday and Tuesday).[9] This regression yields small estimates that are not statistically significantly different from zero for the segment with both TOMs below 7 days nor for the segment with both TOMs larger than 71 days. In other words, I do not find a statistically significant early-sale effect for units in Oslo sold two times in fast-track processes or two times in slow-track processes.

For the segment with twice-sold units when both sales are characterized by medium-track TOMs, there is a statistically significant early-sale effect of a magnitude 1.5 percent of the ask price. The statistically significant estimate of the early-sale dummy is consistent with the hypothesis that the day with the public showing tends to generate intra-week spread differences through a sorting of transactions into fast-track, medium-track, and slow-track processes. I urge caution in the interpretations since the number of observations is larger in the medium-track regression.

The role of ask prices in the early-sale effect

This empirical analysis supports the claim that there is an early-sale effect in the sell-ask spread. To claim that there is an early-sale effect in the sell price, the maintained assumption is that the ask price is an unbiased estimator of the sell price. This assumption makes it possible to control for composition effects by studying the sell-ask spread. I use ask prices in an attempt to control for unobserved heterogeneity. An example of a time-invariant unobserved quality could be an attribute like "view" and an example of a time-varying unobserved quality could be "renovation." While view

[9]Due to the number of observations, I do not include time fixed effects here.

potentially could be captured by unit fixed effects, view might change. Whereas unit fixed effects capture idiosyncratic interior designs, renovation might be time-varying and not captured by unit fixed effects. Ask prices, however, would capture both time-invariant and time-varying unit effects. Thus, ask prices are crucial in this study.

However, the ask price might be biased, contain systematic errors, or be set strategically.[10] Additionally, transaction data do not include observations on units that were not sold, so if systematic errors in ask prices would imply no transactions, we would not necessarily be able to detect them.

Ask-price unbiasedness might not be an innocuous issue, since one potential generating mechanism of the early-sale effect is the ask price itself (Anglin et al. (2003), Genesove and Mayer (2001)). To see how, keep in mind that an ask price constitutes a combination of the seller's market value prediction, loss aversion, strategic price-setting, and reservation price. While the reservation price follows relatively straightforwardly from the seller's match utility, a market-value prediction might contain systematic errors, loss aversion implies stickiness, and strategic ask prices might contain biases. Even if my aim in this article is not to model the formation of ask prices, I shall discuss it.

Since the median sell-ask spread is 0.0 percent (Table 1), it does not appear as if sellers systematically set a low ask price. However, there are asymmetries in the sell-ask spread. The mean is 1.9 percent and the 90th percentile in absolute value is almost twice that of the 10th percentile. Perhaps this can be explained by a tendency among sellers to accept high prices and reject low prices. Another possibility is that the asymmetrical distribution of spreads is linked to a tendency among some sellers to set ask prices low.

It is an empirical question whether market participants would detect biased ask prices and whether the ask-price bias would affect the eventual sell price. Anglin and Wiebe (2013) show that sellers can influence the sell price by choosing a particular level of ask price. If strategically low ask prices lead to more viewers at showings, more bidders in auctions, faster auctions, and different sell prices than non-strategic ask prices do, the ask price itself would be a determinant of the early-sale effect. Then, strategically low ask prices would be part of the selection mechanism that sorted auctions on the showing day into fast-track, medium-track, or slow-track processes. Anglin et al. (2003) inspect the trade-off between ask price and TOM and construct a model in which a higher

[10]It cannot be by much. A regression of the sell price onto the ask price yields an Adj. R2 of 0.974.

ask price implies a longer-than-expected TOM.

There are two competitors for the ask price's position as a gauge of whether a sell price is high or low: the predicted price from a hedonic model and the appraisal value. The former might, however, suffer from possible omitted-variable bias and the explanatory power is lower than that of the ask price. The latter is not available for all units. There are appraisal values for many units in Oslo, but the frequencies are lower in other cities.[11] My view is that although "ask price" might have disadvantages, it is still the preferable variable for my purpose. Below, I use the predicted prices and the appraisal values in a validation exercise.

Validating ask prices using predicted prices and appraisal values

Sell-ask spreads are high when the sell price is high, the ask price is low, or both. Arithmetically, lowering the ask price increases the spread as long it does not lower the sell price more. If the sell price, however, is affected by a biased or strategically set ask price, we must allow for several outcomes: a) the sell price is higher than it otherwise would have been or b) the sell price is lower than it otherwise would have been.

In this article I use a hedonic model to control for errors or strategies in the ask price. We observe from Table 2 that the mean ratio of the ask price to the predicted price varies little across the workweek.[12] Systematically low ask prices do not appear to be a strong candidate for explaining the early-sale effect.

In Table 7, I report results from the same fixed-effect model of Oslo as in Table 5, while using different spreads. If low ask prices play an important role in determining the early-sale effect, we would expect the estimated early-sale-effect coefficient to be different when other spreads are used. This is not the case. The estimated early-sale-effect coefficient of 0.015 for the sell-predicted spread regression is relatively close to the estimated coefficient from the sell-ask spread regression of 0.019 in Table 5.

[11] In Table 1, I report results based on 472,503 observations. Constructing a similar data set for units with available appraisal values yields 260,025 observations. Using that data set, and regressing sell price onto appraisal value yields an R-square of 0.96. In section 3, I reported an R-square of 0.66 for the hedonic model. In Trondheim, the appraisal data set had very few observations.

[12] Saturdays and Sundays are different. However, these days have low transaction volume so I urge caution in interpreting the numbers.

Table 7. Regressions of spreads. Oslo, 2002–2014, exactly 2 transactions

Spreads as dependent variables			
	I	II	III
	Sell-pred	Sell-ask	Sell-appraisal
Early sale (E)	0.0152 (0.0028)	0.0188 (0.0013)	0.0189 (0.0015)
Ask-pred spread		-0.117 (0.058)	
E * Ask-pred spread		-0.0012 (0.0056)	
Time fixed effects	YES	YES	YES
Unit fixed effects	YES	YES	YES
n	13,158	13,158	11,283
T	2	2	2
N	26,316	26,316	22,566
R2	0.0517	0.210	0.166
F-statistic (p-val.)	30 (2.2e-16)	134 (2.2e-16)	94 (2.2e-16)

Notes: "Sell-pred" is short notation for the spread between the sell price and the predicted price as a fraction of the predicted price. "Sell-appraisal" is defined similarly. "T" is the number of transactions per unit. Time fixed effects are captured by time dummies (11 months, 12 years). "Early sale" (E) is a dummy variable. It is unity if the transaction takes place on a Monday or a Tuesday; otherwise zero. White heteroskedasticity-consistent standard errors are computed using the vcovHC function from the "sandwich" package in R. Types HC1 and HC3 yield consistent estimates. I report R2, not Adj. R2. In column III, I trim on the 0.1 and 99.9 percentiles of the appraisal, having included common debt in the appraisal. To test for sensitivity to this choice, I ran a regression on the data set in which I required both transactions to have zero common debt. The pattern was intact.

In Model II, I use the same spread as in Table 5, but include the ask-pred spread, that is, the difference between the ask price and the predicted price as a fraction of the predicted price, and an interaction term as control variables. The idea is to tease out the component of a strategically set ask price from the sell-ask spread, using deviations from the predicted price as an indicator of a strategic ask price. The results of Model II indicate that a strategic ask price might affect the sell-ask spread (naturally), but that the pattern of an early-sale effect is intact. Ask-pred does appear to capture some of the sell-ask spread not captured by the early-sale effect. Since the sell-ask spread can be seen as a combination of a sell-pred spread and a pred-ask spread, including information on the latter should increase the explanatory power if ask prices sometimes deviate from the predicted price. This increase in explanatory power can be seen by the increase in R2, from 0.16 (Table 5) to 0.21 for Model II (Table 7). It appears that ask prices might play a role in explaining parts of the sell-ask spread pattern, but more research is required to state this with confidence.

I also estimate the early-sale effect on the spread between sell price and appraised value (assessed by an external appraiser) using a unit and time fixed-effect model. The transaction data set does not contain appraised values for all transactions, but in Oslo the fraction is high. I find that the estimated early-sale coefficient for Oslo is 0.019, identical to the estimate for sell-ask spreads.

Models I, II, and III support the claim that the early-sale effect exists not only for the sell-ask spread, but also for sell prices.

Sensitivity to seasonality, the business cycle, and specification

Since transaction volumes vary across months (Nenov et al. (2016)) and with the business cycle, it is possible that the results are sensitive to seasonality and the business cycle. I have run the rightmost regression of Table 5 with interaction terms between the early-sale-effect dummy and the dummies for month and year, respectively. I do not report the results. There were few statistically significant coefficient estimates between the early-sale dummy and time dummies and the effects were modest. Overall, the pattern is intact, although the results hint at a reduced early-sale effect in July and in the year 2008, periods of lower transaction volumes.

I have also run the same regression with an interaction term consisting of the early-sale-effect dummy and the most important unit attribute, size. The pattern was intact and the estimated interaction coefficient was statistically insignificant. I do not report the results.

VIII Concluding remarks and future research

I find substantial evidence supporting an early-sale effect on prices in the Norwegian housing market. I study the difference between sell prices and ask prices and find that the difference is higher on Mondays and Tuesdays than on Thursdays and Fridays. The effect is estimated to be on the order of at least one percent of the ask price. In Oslo, the effect is estimated to be larger. I can make the claim of an early-sale effect on sell-ask spreads based on two pieces of empirical evidence. First, I follow units that were sold twice, compute the difference between two spreads, and then take the means across units. I partition the data into segments of transaction days in the first and the second sales. By following the same units, I isolate the effect of the weekday on the sale. Second, I estimate a unit and time fixed-effect model that also controls for across-years cycles and within-year seasonality. The results of these two set-ups yield a range of the early-sale effect on sell-ask spreads: For Norway, the first piece of evidence shows that spreads are between 1.1 to 1.6 percentage points higher than without the effect. For Oslo, the second piece of evidence shows that spreads are about two percentage points higher with the early-sale effect.

I then proceed to ask what mechanism generates this effect. I hypothesize that the effect is linked to the public showing. The idea is that upon arrival at a showing, a prospective buyer learns about the quality of the match between his preferences and the unit's attributes. Units with multiple high-quality matches should experience a faster and more intense auction than units with fewer high-quality matches do. If so, one can expect to find a "day-after-showing effect", that is, an early-sale effect. This finding has several testable implications. First, bidding activity should be higher on days just after a showing. Second, the early-sale effect should occur on other days in cities with other typical showing days.

I find evidence of both. Using data on public-showing frequencies for different cities and data on bidding activity in auctions for different cities, I observe that bidding activity is highest on days after the weekday with the highest frequency of showing. Moreover, the sell-ask spread is associated with a variable that consists of lagging the peak showing day across cities. In a pooled regression of six cities with different public-showing practices, the sell-ask spread tends to be 1.4 percentage points higher on the day after the peak showing day.

I use ask prices, and thus sell-ask spreads instead of only sell prices, to control for a unit's quality, location, and type. After all, the ask price reflects the knowledge of the most knowledgeable agent, the seller. However, the ask price might be biased or strategically set. To check the robustness of the finding, and to substantiate the claim that the early-sale effect also applies to sell prices, not only spreads, I supplement the analyses with estimates on fixed-effect regressions of spreads based on predictions from a hedonic model and on appraisal values from external appraisers. The pattern and estimate magnitudes are intact.

Since my findings support the intuition that high attendance at a showing increases the probability of a high sell price, questions for further research naturally revolve around determinants of high attendance and which role, if any, ask prices could play. It is also natural to ask how, in the future, virtual inspections on-line would affect the early-sale effect. Moreover, in the extension of my findings, questions arise on how buyers search, what strategies they use in bidding, when sellers decide to hold a new auction or pull the unit from the market, what role TOM plays, and whether units with unique attributes gain or lose by being put on the market in periods with high transaction volumes.

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X Appendix

Table A1. Sell-ask spread for segments of TOM. Fast-track, medium-track, and slow-track sales, Oslo, 2002–2014. 2 transactions

Panel A: Mean spreads (st.dev.) for segments of TOM

	Fast-track: < 7		Medium-track: $7 \leq TOM < 12$		Slow-track: > 71	
Day	N	Spread	N	Spread	N	Spread
Sun	20	0.071 (0.053)	33	0.095 (0.074)	24	-0.026 (0.057)
Mon	865	0.088 (0.084)	4,127	0.085 (0.078)	621	-0.004 (0.087)
Tue	462	0.071 (0.076)	4,040	0.071 (0.077)	606	-0.010 (0.071)
Wed	236	0.084 (0.084)	1,247	0.054 (0.078)	543	-0.022 (0.070)
Thur	215	0.094 (0.086)	605	0.056 (0.091)	366	-0.019 (0.066)
Fri	163	0.094 (0.080)	777	0.073 (0.089)	402	-0.024 (0.066)
Sat	16	0.102 (0.056)	63	0.055 (0.059)	40	-0.024 (0.053)
N	1,977		10,892		2,602	

Panel B: Regression: Spread regressed on

	Both sales fast-track	Both sales medium-track	Both sales slow-track
Early sale (E)	-0.020 (0.021)	0.0145 (0.0038)***	0.0173 (0.010)
Unit FE	YES	YES	YES
No. obs.	85 (170 sales)	2,350 (4,700 sales)	184 (368 sales)
R2	0.013	0.0066	0.013
F-stat. (p-val.)	1.14 (0.289)	15.6 (8.2e-5)	2.37 (0.125)

Notes: Segmented on units in Oslo with exactly two transactions. Panel A segments on transactions whereas Panel B segments on units. Thus, in panel A, one or two sales of a unit might be included. In panel A, the partitioning is done on percentiles of transaction TOM (measured in days). In panel B, the partitioning is done on units in which both transaction TOMs satisfy the partition criterion. I report R2, not Adj. R2, since the number of intercepts is high in the unit fixed-effect set-ups. Fast-track sales are defined as sales with a TOM below 7 days (10th percentile of TOMs), medium-track sales are defined as sales with a TOM larger than or equal to 7 days and below 12 days (median), and slow-track sales are sales with a TOM of more than 71 days (90th percentile). "Early sale" is a dummy variable. It is unity if the transaction takes place on a Monday or a Tuesday; otherwise zero. Panel B standard errors are White heteroskedasticity-controlled estimates from the vcovHC function in the "sandwich" package in R. Types HC1 and HC3 yield consistent estimates. The term "***" is a short notation for significance on the 0.001 level.

Table A2. Weekday frequency (percent) of public showings, 6 cities, 2013–2017

	Sun	Mon	Tue	Wed	Thur	Fri	Sat	Sum Sun-Sat
Oslo	44.1	30.2	12.2	4.1	8.5	0.2	0.7	100.0
Bergen	13.2	18.6	26.8	24.9	16.0	0.1	0.3	100.0
Trondheim	1.3	18.7	29.2	40.5	10.1	0.0	0.1	100.0
Kristiansand	1.0	6.8	23.5	37.6	29.4	0.7	1.0	100.0
Stavanger	23.7	27.7	24.8	15.0	8.3	0.1	0.4	100.0
Drammen	34.7	24.6	9.8	6.2	17.4	0.0	7.4	100.0

Table A3. Weekday frequency (percent) of bidding, 4 cities, 2011–2016

	Sun	Mon	Tue	Wed	Thur	Fri	Sat	Sum Sun-Sat
Oslo	1.7	27.3	38.9	18.0	6.3	7.5	0.3	100.0
Bergen	0.8	5.8	18.2	38.8	21.3	14.3	0.7	100.0
Stavanger	0.5	14.8	22.6	21.3	21.2	19.3	0.3	100.0
Drammen	2.5	35.5	28.8	16.1	7.5	9.2	0.6	100.0