The most wonderful time of the year? Thin markets, house price seasonality, and the December discount*

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Abstract

In Norway, house prices tend to drop in December. This regularity could be caused by a composition effect, a seller effect, or a thin market effect. This article exploits a high-resolution transaction data set with exact sell dates to demonstrate the existence of a December discount. To show existence, we deal with unobserved unit and seller heterogeneity using unit fixed effects, ask prices, and appraisal values. We examine generating mechanisms and find that cross-sectional evidence supports a thin market effect. We find no evidence of stressed sellers. Examination of bidding behavior in a bid-by-bid micro auction data set indicates that sellers grow impatient as the holiday season nears. Scrutiny of seller behavior in advertisement data shows reduced activity on the supply side in December.

Keywords: auction bids, house price seasonality, impatience, stressed sellers, thin markets

JEL Codes: C21, D12, R31

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1 Introduction

In Norway, mean house prices drop every December. At first blush, this price reduction could encourage people to buy in December and discourage people from selling in December. However, on second thought, houses that transact in December might simply be different from houses that transact in August. If such a composition effect accounts for the whole difference, the price drop is no discount nor is there any special buying opportunity. In order to account for the magnitude of the composition effect, we start out using a hedonic model to control for house attributes so that we obtain a quality-controlled estimate of the December disocount. There are, however, challenges from unobserved unit and seller heterogeneity. We deal with these challenges in order to ask: Is there really a December discount? If yes, what generates it?

The answer to the first question is that, yes, there is a December discount and its magnitude is at least one percent. It appears to be generated by thin markets and impatient sellers. To arrive at these findings, this article exploits two data sources, a repeat-sales data set and an auction bidding data set. We use repeat-sales to control for unit-specific factors by following the same housing units over time and we employ the ask price to account for time-varying omitted variables of the housing unit. We use the appraisal value as instrument to control for seller-specific effects and the auction bidding log of individual sales to uncover the degree of impatience among sellers.

The novelty of our study lies in the temporal resolution of sales (precise down to the day) and fine granularity of bids (precise down to the minute). We access the exact date when an individual unit is announced for sale. We also acquire the exact date on which a bid is accepted by a seller, which in Norway constitute transfer of ownership since both bids and acceptances of bids are legally binding. For each bid individual buyers make, we have the date and the time of day. Our contribution is purely empirical and consists essentially of three elements. First, we are able to exploit the information on exact dates to demonstrate seasonality in house prices while controlling for unobserved heterogeneity. Second, we make use of the differences in different sub-markets in Norway to identify an association between price seasonality and volume seasonality and market heterogeneity. Third, we are able to construct a gauge of impatience by inspecting the bid-by-bid dynamics in auctions and show that this gauge shows seasonality.

Such findings are relevant to economists and policymakers for at least three reasons. First, ours is a case study of search and matching activity, an activity meticulously studied in labor economics, and less studied in the housing market. While changing jobs requires a worker to find a new employer, moving house involves dual search in that it requires that the moving owner-occupier find both a seller and a buyer. Knowing factors in the determination of this search and matching in the housing market is a necessary first step if one wants to understand and improve the process. Second, the estimate of a one percent December discount due to thin markets and seller impatience allows policymakers to entertain some ideas on the societal value of arranging markets such that house attributes are aligned with preferences without long time-on-market periods. After all, a non-trivial portion of all sales take place in December and the overall value of the housing stock in Norway is estimated to be almost 2.5 times its GDP.[1] In other words, even one percent matters. Third, it is a test of the implications in Nenov, Røed Larsen, and Sommervoll (2016) that transaction volume seasonality implies price seasonality.

Our empirical strategy is straightforward. We use a hedonic model to account for the composition effect. To control for the time trend in house prices, we use both year fixed effects and estimates of trend-lines. The December discount survives these initial controls. We go on to employ a unit fixed effect model to accont for permanent unobserved unit heterogeneity. To that end, we study units that have been sold twice. We use the ask price to account for temporary unobserved unit heterogeneity, in case the unit has been renovated or has deteriorated between sales. We use the appraisal value as an instrument

[1] This is a back-of-the-envelope computation using the following numbers: The Norwegian GDP for the year 2017 in market value is 3,300 billion NOK; see http://www.ssb.no. The firm Eiendomsverdi computed the market value of the Norwegian housing stock in September 2017 to be 8,000 billion NOK (contact eiendomsverdi.no).

for unobserved seller heterogeneity, in case different seller types tend to set the ask price differently. Moreover, we also employ a segmentation technique, in which we sample units that have been announced for sale in August and September so that we avoid possible a self-selection mechanism that sort sellers into a group consisting of sellers who sell early in the Fall and another group consisting of sellers who decide to sell late in the Fall.

To study whether thin markets is a generating mechanism, we partition Norway into sub-markets. We use 428 municipalities and divide every municipality into different more sub-markets using types and sizes. We retain sub-markets with a sufficient number of transactions, which leaves us with 231 sub-markets. We characterize these markets along degrees of price seasonality, volume seasonality, and horizontal differentiation[2]. Regressing a measure of price seasonality on measures of volume seasonality and horizontal differentiation shows that price seasonality is associated with volume seasonality and degrees of horizontal differentiation (market heterogeneity). To study a stressed seller mechanism, we look for discontinuities using a regression discontinuity design (RDD). We study sell-ask spreads, sell-appraisal spreads, and survival rates. We find no discontinuities. To study seller impatience, we use the auction bidding data to find, in every auction, the highest non-winning bid extended a period before the highest bid was accepted. Then, we measure the monetary difference between the winning bid and the earlier non-winning highest bid. We suggest that this difference informs us about seller impatience since an impatient seller would tend to accept a bid that was not much higher than the earlier declined bid. The frequency to accept bids that are not much higher than declined bids becomes higher in December.

Our idea that a thin market mechanism may be a possible explanation of the December discount builds on search theory and involves the number of market participants (Ngai and Tenreyro (2014); Kaplanski and Levy (2012); Nenov, Røed Larsen, and Sommervoll (2016); and Novy-Marx (2009)). The notion we use is that fewer sellers and fewer buyers lead to

[2]We define vertical differentiation as differentiation in which there exists an observable attribute along which everyone agrees on the ranking. For example, larger is preferable to smaller. We take horizontal differentiation to mean differentiation in which there exist a quality over which individual tastes matter and there is no agreement.

lower-quality matches between units and buyers. We describe a skeleton model that outlines our reasoning and use the search literature (Diaz and Jerez (2013), Genesove and Han (2012), Kashiwagi (2014), Maury and Tripier (2014), and Krainer (2001)) to show how to derive a probability of a high price. Another possible explanation of the December discount, however, is that December-sellers are stressed due to a, financially or otherwise sourced, year-end deadline. Sellers could thus be prevented from holding their units until market activity surges in January. This is not implausible. Moving owner-occupiers who bought first, and thus hold two houses in the transition periods, need to service two mortgages. Banks could ask them to off-hand the old house and complete the sales and insist they will not renew the interim financing of holding two houses. According to this hypothesis, sellers would offer discounts to attract buyers and speed up the time-on-market. We also outline a model sketch of how we think about this possibility. Both mechanisms may, of course, be at work at the same time. In fact, we propose that a third mechanism also may be in play, a seller impatience mechanism. This could be a self-imposed desire to sell before the holiday season nears and start the new year with clean sheets.

This article is structured thus: Section two goes through the empirical methodology. Section three presents the data sources and specific metrics employed. Section four contains empirical results. In section five we present our skeleton models that rationalize what we have observed. Section six presents evidence of our skeleton models of what generates the December discount. Section seven discusses how to probe deeper into the demand and supply sides using auction and advertisement data. Section eight concludes.

2 Estimation methodology

2.1 Employing ask price and appraisal value to construct a proxy for latent quality

The sell price of house h, SP_h, is a function of observed attributes A_h for house h, unobserved quality ξ_h, a December discount D_h, and a residual component ϵ_h:

$$SP_h = a + bA_h + c\xi_h + dD_h + \epsilon_h, \tag{1}$$

in which ϵ_h contains both a match-utility component that is sourced from the unique matching between attributes of unit h and buyer preferences, non-observable seller-specific components, and a mean-zero, constant variance white noise element. For simplicity, we suppress the subscript t (time) for now.

The hypothesis that a December discount exists is the hypothesis that the coefficient d is statistically significantly different from zero and negative. If c or ξ_h is non-zero, OLS suffers from omitted variable bias, and if the prevalence of ξ_h in December-sales is different from its prevalence in non-December-sales, the OLS estimator of d is biased. In an OLS-regression of sell price onto attributes and a December-dummy, we would risk that a selection mechanism would make units with certain ξs be associated with a December sale. In order to address this problem, we employ several fixes. We deal with time-invariant unit heterogeneity using a unit fixed effect model estimated on repeat-sales data. We deal with time-varying unit heterogeneity using ask prices to capture quality aspects of the unit. The ask price is set by the seller in collaboration with the realtor.

The seller is the agent with the most knowledge about the unit h. He sets an ask price, AP_h as a function of observable attributes A_h and unobserved quality ξ_h since he knows this quality:

$$AP_h = \alpha + \beta A_h + \gamma \xi_h + \mu_h, \tag{2}$$

in which μ_h is an error term composed of other terms, including seller sentiment.

We cannot substitute ask price for the latent variable ξ since ask price could be endogenous, i.e. it could be correlated with the error term ϵ_h since ϵ_h may include a seller-specific component such as propensity-to-sell, impatience, strategy, or value bias. AP_h may not be orthogonal to ϵ_h. We propose to deal with unobserved seller heterogeneity using appraisal as an instrument. Since selling fast could reveal seller strategy, we also use time-on-market (TOM) as an instrument.

We obtain a predicted ask price by performing a first stage regression:

$$AP_h = \pi_{10} + \pi_{11} AV_h + \pi_{12} TOM_h + +\pi_{13} A_h + \mu_{1h}, \tag{3}$$

in which A_h represents a vector of unit attributes and in which appraisal value AV_h is exogenous. The appraisal value is set by an independent appraiser.[3] When the logarithm of ask price is used, we use the logarithm of appraisal value and attributes. In Table 4 below, we use log(appraisal) and log(size). Time-on-market (TOM) may contain relevant information on the sell price since it reflects buyer preferences. It is determined by a multivariate market process involving the arrival rate of buyers' bids, which is exogenous to the elements in ϵ. However, TOM may contain elements that are not orthogonal to ϵ since ϵ may contain seller-specific factors that also affect the decision of when and at what price to sell. In a sensitivity section, we study the validity of including TOM in the first stage. An alternative approach, predicts ask price AP from regressing it on appraisal value AV and other variables (including

[3]See norsktakst.no or nito.no/english for online descriptions of Norwegian appraisers.

attributes). The predicted ask price, $\hat{AP}_h$, is used as a proxy for the latent variable quality, ξ_h, and allows us to control for unobserved unit heterogeneity. We regress sell price onto a space spanned by observable attributes, the predicted ask price $\hat{AP}_h$, and a December dummy. The resulting estimate of the December discount, $\hat{d}$, is unbiased given the model.

2.2 Employing a repeat-sale set-up to control for unit-specific elements

An alternative to using ask price, appraisal value, and predicted ask price as proxy for unobservable quality, is to use a repeat-sale set-up. In the repeat-sale set-up, we follow the same unit over time and may thus estimate the December discount by including a unit fixed effect that captures time-invariant unit heterogeneity:

$$SP_{h,t} = a_h + dD_{h,t} + \epsilon_{h,t}, \tag{4}$$

in which a_h is a unit-fixed intercept, t is time, and $\epsilon_{h,t}$ is a zero-mean, constant-variance stochastic variable. Regressing sell price SP onto a space that includes a dummy for a December-sale allows us to obtain another estimate of d. However, latent quality $\xi_{h,t}$ may contain both a time-invariant element and a time-variant element. While the unit fixed effect model only controls for the time-invariant element, using the predicted ask price from the appraisal value controls for both time-variant and time-invariant elements.

3 Data and empirical techniques

3.1 Data sources

This article employs three data sources: transaction data, advertisement data, and auction data.

From the collaboration with real estate agencies, *Eiendomsverdi* obtains information on units advertised for sale on the on-line platform *Finn.no* that covers more than 70 percent of the market. This source includes both units that are sold and units that are never sold. The former are transaction data and the latter are used to construct the advertisement data. The data are combined, and cross-checked, with public registry transaction data. The transaction data are similar to the data used in Anundsen and Røed Larsen (2018) and Røed Larsen (2019), and include, but are not limited to, unit identifier, transaction price, common debt, ask price, date of acceptance of highest bid, date of advertised for sale, address, GPS-coordinates, unit attributes (e.g. size, construction year, number of rooms), amenities and neighborhood specifics (distance to water, estimated sunset in June).

We trim the data by removing observations with missing values, duplicates, suspicious entries, and typos. Common debt is included in sell price, ask price, and appraisal value. We trim on 0.1 and 99.9 percentiles on sell price, size, sell price on size, and sell-ask spread. We remove co-ops. We construct two data sets: i) part I by removing all observations without appraisal values and ii) part II by including observations without appraisal value (see below). For part I, we also trim on 0.1 and 99.9 percentiles of the sell price on appraisal value ratio. This leaves us with 279,840 observations with appraisal value. They constitute the core data and are summarized in Table 1. Depending on the purpose, we truncate on different variables, e.g. month of announcement of sale, sell date, and TOM. Then we explain the truncation in a footnote.

Table 1. Summary statistics. Transaction data. Norway, 2002-2014

	Min	25th percentile	Median	Mean	75th percentile	Max
Sell	325,000	1,595,000	2,200,000	2,549,248	3,100,000	12,150,000
Ask	300,000	1,560,000	2,150,000	2,503,803	3,000,000	12,100,000
Size	20	73	108	116	150	363
Sell/size	3,113	14,762	22,033	24,872	32,292	79,773
Date	1 Jan 2002	27 Jan 2006	28 April 2008	NA	18 Oct 2011	1 Feb 2014

Note: Prices are in NOK. Size in square meters. Date is date of acceptance of bid.

The data on advertisement are acquired by Eiendomsverdi from the same sources, Finn.no and real estate agencies, and are constructed as monthly counts of new advertisements. The period covered is January 2009-February 2017.

The data on auction bids ares sourced from DNB Eiendom, a realtor branch of Norway's largest bank, DNB, and cover the period 2007-2017. The data set includes detailed information on every bid placed in every auction. We study 125,986 auctions that resulted in a sale. We have information on each bid, including a unique bidder id, the time at which the bid was placed (with precision down to the minute), and the expiration of the bid (with precision down to the minute). Additionally, the data set contains information on the ask price, appraisal value, attributes of the unit, and the number of visitors to people the public showing. Since the appraisal value ceased to be obtained in 2016, and since appraisal value was not obtained in every auction before 2016, conditioning on existing appraisal value reduces the size of the data set.

3.2 The longitudinal and cross-sectional structure of the data

In the longitudinal structure of the data, we follow units across repeat-sales and order the data to be sorted by units and number of sale. We retain owner-occupied units and drop co-ops. In order to employ appraisal value as instrument, we retain observations with information on appraisal value.

In the cross-sectional sub-market analysis, we order the data on transactions, not units. We include also observations without appraisal value. When we study geographical variation, we first keep the municipalities with at least 1,000 transactions over the period out of a total of 428 municipalities. We then partition into three types of units: detached, apartments, and semi-detached/row houses. In the second partition, we use size to partition into two groups: i) lower than median and ii) larger than or equal to the median. We then retain segments with at least 500 transactions. The maximum number of segments are: 428 municipalities times 3 types times 2 sizes, i.e. 2,568. Out of these permutations, 101 municipalities have at least 1,000 transactions. Out of the remaining 606 municipalities*types*sizes, the final truncation requires at least 200 transactions in the sub-segment. This leaves us with 231 sub-segments with 449,719 transactions to study. The transactions in this data set comprise 41.3 percent detached units and 37.2 percent apartments.

3.3 Cross-sectional regression analysis

3.3.1 Price seasonality across sub-segments

For each of the 231 segments, we construct a measure of price seasonality. For each year, we compute the mean sell price in December and the mean sell price across the remaining 11 months. Then we compute the ratio of these two means, which is a measure of that year's price response in December in each segment. For each year in each segment, we also compute the mean transaction volume in December and the mean transaction volume for the whole year. The ratio is a measure of seasonality in the number of transactions in that segment. For both measures, we compute the average across the period of 12 years for each segment. Thus, for each segment s = 1, ..., 231, we obtain a measure of its price seasonality PS_s:

$$PS_s = 1 - \frac{\sum_{y=2002}^{2013} \frac{\sum_h SP_{s,y,Dec,h}}{\sum_h SP_{s,y,\neg Dec,h}}}{12}, \quad s = 1, ..., 231, \tag{5}$$

in which the subscript h refers a housing unit transaction within the relevant period in the relevant segment s, SP is sell price, and the use of the logical negation symbol $\neg$ in $\neg Dec$ means all months except December, i.e. January-November. The lower the December prices are, the higher the price seasonality will be.

For each segment s, we also obtain a measure of transaction volume seasonality VS_s:

$$VS_s = 1 - \frac{\sum_{y=2002}^{2013} \frac{N_{y,Dec}}{N_y}}{12}, \quad s = 1, ..., 231, \tag{6}$$

in which N refers to the number of transaction observations within the relevant period. We use all sales in the year in stead of all sales in the period January-November because then the interpretation of the measure is a monthly share of annual sales. The lower the transaction volumes in December, the lower that month's share, and then the higher the volume seasonality.

We then construct a measure of horizontal differentiation, i.e. the preference differences among buyers on certain attributes, for each of the 231 segments As Nenov, Røed Larsen, and Sommervoll (2016), we measure horizontal differentiation in a segment s using unity less the adjusted r-squared from a hedonic regression of all sell prices in that segment s, $HD_s = 1 - Adj.R^2_s$. The adjusted R-square is obtained from a hedonic regression of the logarithm of sell price onto a space spanning determinants:

$$log(P_{h,t}) = \alpha + \beta_1 log(size_h) + \beta_2 (log(size_h))^2 + \sum_m \gamma_m MD_{h,t} + \gamma_y Y_{h,t} + \sum_{cp} \theta_{cp} CPD_t + e_t, \tag{7}$$

in which eleven month dummies γ_m capture the within-year seasonal effects, the year coefficient γ_y captures a linear price trend, and the three dummies for construction period θ_{cp}

captures both epoch building style and age of the unit. The subscript t refers to transaction time and e_t is an error term. The vector variable $MD_{h,t}$ consists of 11 variables; unity for unit h in the month of transaction; otherwise zero. The variable $Y_{h,t}$ is a year counting variable. It takes on the year number in the period the sale of unit h took place, i.e. the difference between the transaction year and the starting year, e.g. 2010 - 2002 = 8. The variable CPD_t consists of epoch dummies that for a unit h takes the value one if the unit was built in the period. Since we run 231 regressions, we choose a parsimonious model to avoid over-fitting, missing values, interaction sensitivity, and robustness issues.

We run seasonality OLS regressions over 231 segments:

$$PS_s = \lambda_1 VS_s, \qquad s = 1, ..., 231. \tag{8}$$

$$PS_s = \lambda_2 HD_s, \qquad s = 1, ..., 231. \tag{9}$$

These regressions constitute the tests of thin market effects. The first regression tests the hypothesis that sell prices are associated with transaction volumes since sell prices tend to be higher when there are more sellers and more buyers, i.e. higher market activity. The underlying idea is that higher market activity is associated with a higher likelihood of high-utility matches, as outlined in the parsimonious search-and-match model presented below. If matching is the core of the mechanisms behind a December discount, a price seasonality drop in December would tend to be stronger the stronger the volume seasonality. Likewise, price seasonality would be stronger the more horizontally differentiated the segment is since horizontal differentiation requires more buyers per seller in order to result in a high-utility match.

4 Empirical results

4.1 The regularity of a December drop

We construct two hedonic models to control for composition effects. Model I captures time effects by including dummies for 12 sales years and 11 sales months, in addition to a number of attributes. Model II captures time effects by including a trend-line, using a month counter that runs from 1 to 146.

In model I, the coefficient of December sales is easily compared to coefficients of November and October. The coefficient estimate for December in Table 2 is clearly lower than coefficients for earlier Fall months, indicating that December sell prices are lower than previous months. A December transaction is associated with a 2.1 percent lower sell price than a November transaction ($e^{(0.019-0.040)} = 0.979$). Comparing a December-dummy estimate with a January-dummy estimate would be less informative if there is an increasing trend throughout the period. The reason why is that January in year t is 11 months earlier than December in year t. Then the rising trend would not properly be modeled by year dummies since the year dummy would only capture the level in year t, i.e. the mid-point that occurs around July. In fact, then month dummies would contain two effects, the calendar (season) month effect relative to default (July) and a within-year linear trend. If the linear trend is sufficiently strong, a positive trend effect could dominate a negative season effect and possibly lead to a higher December estimate than a January estimate. In fact, in model I we do observe that the January dummy estimate is lower than the December dummy estimate.

Thus, this article also estimates a simple linear trend, using a counter for month number throughout the period and calendar month dummies. We observe that for Model II the December estimate of -0.0037 is lower than both the November estimate of 0.0221 and the January estimate of 0.0399. The high estimated standard error of the December estimate implies a low t-value of 1. However, in this context the interpretation is that the December dummy estimate is not statistically significant from zero, i.e. the default period, which is July. The December dummy estimate is statistically significant from both the January estimate and the November estimate. Moreover, the December dummy estimate is much lower than estimates for all Fall months.

Table 2. Hedonic model of log sell prices on determinants. Norway, 2002-2014

	I	II
Intercept	12.4 (0.12)	12.4 (0.12)
Logsize	-0.130 (0.05)	-0.150 (0.05)
Sqlogsize	0.090 (0.005)	0.092 (0.005)
Type FE	YES	YES
Interaction	YES	YES
Constr. year	YES	YES
City FE	YES	YES
Region FE	YES	YES
Sales year FE	YES	NO
Month No.	-	0.00481 (1.4e-5)
Feb-June FE	YES	YES
Jan	0.014 (0.003)	0.0399 (0.003)
Sept	0.057 (0.003)	0.0488 (0.003)
Oct	0.044 (0.003)	0.0311 (0.003)
Nov	0.040 (0.003)	0.0220 (0.003)
Dec	0.019 (0.004)	-0.0038 (0.004)
Degrees of freedom	260,966	260,977
(Deleted due to missingness)	(18,811)	(18,811)
Adj. R2	0.715	0.710
F-statistic (p-value)	1.05e4 (2.2e-16)	1.25e4 (2.2e-16)

Note: White heteroskedasticity-consistent standard errors, computed using the R-function vcovHC. Interaction variables comprise products of (Oslo,logsize), (Oslo, sqlogsize), (apartment, logsize), and (apartment, Sqlogsize). The specification also includes construction year. In model I, the fixed effects include dummies for each month and year. July is default for month and 2002 for year. In model II, July is default for month and Month No is sales month number, counted from January 2002. It runs from 1 to 146 and represents a trend increase. We also examined the results from a second order polynomial in Month No.

The main pattern is intact.

4.2 Regression discontinuity design

Table 2 demonstrates that in a hedonic model with time dummies or time trend, December sales are associated with lower sell prices. The result, however, is sensitive to omitted variable bias, caused by unobserved unit heterogeneity. If negative unobserved qualities are associated with December transactions, the December dummy estimate contains both a season effect and a quality effect. In this section, we employ two techniques: a) the ask price as a proxy for latent quality and b) a temporal selection of units.

We perform several variations of regressions in which the logarithm of sell price is the dependent variable. In the regressions we use sub-sample of the data that has been selected on transaction date and advertised date. The data are limited to units that were announced for sale in August-September and sold in August-December. The idea is that a December discount is a discount on units that were announced for sale in August and September, but for which the sale processes took a long time. Thus, we start out by examining data in which the unit was announced for sale in August or September and we look for indications that sellers of units contemplate discounts as time-on-market increases. Thus, in model I in Table 3 we specify the most parsimonious model consisting of Days since 1 Aug and the interaction variable December-dummy times Days since 1 Aug. This is a regression discontinuity design in which the former variable captures the downward price trend in the Fall and the latter captures the potential change of slope in December. Below, we explore this in more detail by comparing the development as time-on-market increases of multiple metrics for units announced for sale in different months.

Within this period, 1 December is day number 123 and 31 December is day number 153. The estimated coefficients are -1.46e-3 and 7.37e-5, showing a downward trend that becomes less steep. The estimated coefficient of the interaction term December*Days has the wrong sign for a distressed seller hypothesis, but is statistically insignificant. Transactions in

December are associated with lower sell prices, i.e. selling on 10 December is associated with a lower price than selling on 1 December, but the price difference is smaller than between 1 November and 10 November.

Table 3 tabulates regression results from three additional regressions. In the augmented Models III and IV, we include the logarithm of ask price. The estimated coefficient is close to unity, indicating that the ask price is highly informative of the sell price. The negative estimate of the coefficient of size may at first seem puzzling, but is simply a result of the fact that the ask price already reflects size.

Careful interpretation of the estimates in these models requires some additional numerical comments. For the parsimonious Model I, the partial derivative, $\partial log(sell)/\partial Days$ is 123(-1.46e-3 + 7.71e-5), or -0.170, on 1 December. Ten days later it is -0.184. In Model III, in which the hedonic model controls for attributes and location, the derivatives are smaller in absolute value: -0.107 and -0.112, respectively. These estimates represent factors of $e^{-0.107} = 0.902$ and $e^{-0.112} = 0.894$, e.g. a reduction in sell price of 100(1-(0.894/0.902)) = 0.89 percent. A transaction date delayed by ten days is associated with an nine tenths reduction in sell price. The results in Table 3 demonstrate decreases in prices, but a fair reading leads one to interpret the findings as more gradual than discontinuous. In fact, these results do not appear to be consistent with a hypothesis involving seller becoming distressed at at particular day in December. The contrary is a more natural interpretation: these results are consistent with mechanism that gradually increases during the Fall.

Table 3. RDD regressions of log(sell price), December slope-dummy

	OLS of log(sell price) on			
	I*	II*	III*	IV**
Intercept	14.7 (5.0e-3)	12.7 (1.6e-2)	1.80e-1 (9.8e-3)	2.73e-1 (1.3e-2)
log(size)		0.44 (3.6e-3)	-1.85e-2 (7.1e-4)	-3.31e-3 (1.5e-3)
log(ask)			9.81e-1 (7.4e-4)	9.87e-1 (1.1e-3)
Type FE				YES
City FE				YES
Sale Year FE				YES
Construction Year FE				YES
log(size)*Type				YES
log(size)*City				YES
Days since 1 Aug	-1.46e-3 (9.1e-5)	-2.45e-3 (8.3e-5)	-1.03e-3 (1.2e-5)	-9.93e-4 (1.3e-5)
Dec*Days since 1 Aug	7.71e-5 (1.2e-4)	3.01e-4 (1.1e-4)	1.60e-4 (1.5e-5)	1.60e-4 (1.7e-5)
Sell months in sample	Aug-Dec			
Announced for sale	Aug-Sep			
N	56,413	56,413	56,413	56, 056
Adj. R2	0.0055	0.181	0.981	0.982

Notes: * White HC-standard errors. ** Classical standard errors. Truncation on TOM < 153, announced for sale in August and September and transacted in August-December.

4.3 IV-approach

A challenge with the RDD approach is the possible endogeneity of ask prices. Ask prices may be correlated with omitted variables and thus the error term since the seller knows about the latent quality, sets the ask prices, and also makes the decision on whether or not to accept a bid. In this section, we employ instruments in an 2SLS-approach to deal with unobserved seller heterogeneity. We run a 2SLS regression of log(sell) on log(size), log(ask), and a December-dummy while using as instruments for log(ask) these variables: log(appraisal value), log(size), time-on-market (TOM). In Model V, we exclude transaction dates in August and September and include only transactions in October, November, and December.

Table 4. IV-model of log(sell price) on regressors. Transaction months Aug-Dec, Oct-Dec

	OLS			2SLS	
	I	II	III	IV	V
Intercept	12.69 (0.011)	0.0918 (0.0071)	0.229 (0.011)	0.0684 (0.0063)	0.0761 (0.0088)
log(size)	0.417 (0.0025)	-0.0299 (0.00051)	-0.0095 (0.0012)	-0.0308 (0.00049)	-0.0297 (0.00069)
log(ask)		1.004 (0.00054)	0.987 (0.00091)	1.0062 (0.00048)	1.0050 (0.00066)
Type FE			YES		
City FE			YES		
Sale Year FE			YES		
Construction Year FE			YES		
log(size)*Type			YES		
log(size)*City			YES		
December	-0.0822 (0.0050)	-0.0168 (0.00079)	-0.0161 (0.00078)	-0.0166 (0.00081)	-0.012 (0.00084)
Sell months in sample	Aug-Dec	Aug-Dec	Aug-Dec	Aug-Dec	Oct-Dec
N	115,756	115,756	114,877	115,792	60,052
Adj. R2	0.163	0.979	0.979	0.979	0.979

Note: We truncated data on TOM < 200 to avoid having ultra-long TOMs affect estimates. Estimation results without the truncation are, however, highly similar. In Model IV, instruments are log(size) (for itself), December dummy (for itself), log(appraisal) and TOM. The standard errors for the OLS regressions are White heteroskedasticity-consistent errors computed in R using the vcovHC-function from the lmtest package. To estimate Models IV and V, we use the ivreg-function in the AER-package in R and report the outputted standard errors.

We observe from Table 4 that the estimate of the December dummy varies with specification. We notice that the most parsimonious model, Model I, has an estimate that is large in absolute value, -0.082. Model II includes log(ask price) and thus controls for the composition effect, and then we observe that the estimate of the December dummy falls in absolute value, to -0.0169, indicating that there are substantial composition effects in the Fall months. However, the December discount still survives the control for composition since it is highly statistically significant. In fact, the estimates of the December dummy from Models II-V have a relatively small range. They range from 1.7 percent discount to 1.2 percent discount, thus the discount is insensitive to specification and relatively robust to data truncation.

4.4 A unit fixed-effect model

This sub-section employs a unit fixed-effect model to account for unobserved unit heterogeneity, i.e. possible idiosyncratic elements in the units. To this end, we study data in which units are transacted exactly twice. Units can be classified into three categories: i) both sales in December, ii) one sale in December, or iii) no sale in December. We regress log(sell price) onto a space that consists of a December dummy and a number of other determinants. We use predicted ask price from a regression on appraisal value. In the fixed effect model, we control for time-invariant features using the FE-estimator and time-variant features employing the logarithm of either ask price or appraisal value. Results for Models I-V are reported to perform show coefficient estimate sensitivity and to uncover what variables contribute to explanatory power. Model IV is the fully specified model, from which we obtain our most accurate estimate of the December-discount.

Table 5. Log(sell) on regressors. OLS, FE, and FE/IV models

	Log(sell) regressed on					
	OLS	Fixed Effect			FE/IV	FE
	I	II	III	IV	V	VI
Intercept	14.6***					
December	-0.076***	-0.024***	-0.0042	-0.010***	-0.0064*	-0.010***
Unit FE	NO	YES	YES	YES	YES	YES
Time FE	NO	NO	YES	YES	YES	YES
Log(ask)				0.821***		0.822***
Log(ask) instrumented					0.236***	
Log(appraisal)						-0.0018
No. obs.	146,228	74,030	74,030	74,030	74,030	74,030
No. repeated	-	2	2	2	2	2
Adj. R2	0.00088	0	0.619	0.865	0.677	0.865

Notes: Time fixed effects are 12 year-dummies (2002 is default) and 3 quarter-dummies (1st quarter is default). The fixed effect models are estimated using the plm-function and the "within"-model option in R's plm-package. ***,**,* is short notation for the absolute value of the t-statistic > 2.5766, 2.326, and 1.96, respectively. The t-statistic is computed as a ratio of the coefficient estimate on estimated White HC-standard error (from the vcovHC-function in R's lmtest-package). Log(ask) on IV is the predicted value from regressing log(ask) on log(appraised value).

We observe in Table 5 that the estimated December effect is negative for all six models. Since these models (except Model I) include a unit fixed effect, the concern over a possible endogeneity of the log(ask)-variable should be alleviated. Moreover, Model V instruments the log(ask) using the exogenous appraisal value and Model VI includes the log(appraisal) as a corrective to the log(ask).

The best fit is offered by Model IV and Model VI, both including the variable log(ask). The good fit reflects the importance of the ask price in accounting for unobserved unit heterogeneity. The ask price captures unit qualities that hedonic attributes do not capture. This is further supported by observing the much lower estimated coefficient, 0.235, of the log(ask) in model V, in which we instrument log(ask) by first regressing it on log(appraisal) then inputs the predicted value. We also observe that there is no increase in explanatory when we add log(appraisal) to Model IV and obtain Model VI. The interpretation is that the seller's information, through log(ask), includes all the information appraisal values contain.

The two best-fit models, Models IV and VI, yield an estimated December-effect on log(sell) of -0.01. This estimation implies that a given unit, when sold in December, tends to obtain a sell price that is ($e^{-0.01} =$) 0.990 of the sell price it tends to obtain if it is not sold in December. Thus, the FE model approach estimates the December-discount at 1 percent.

5 Exploration of generating mechanisms

5.1 Skeleton model of search and match-utility

Above we have established that there is a December discount. It implies that when a unit is sold in December it sells for a price that is lower than the price had been if the same seller had sold the same unit in November or January. In this section, we outline a framework we use when we investigate possible generating mechanisms. It builds on the model in Anundsen and Røed Larsen (2018) and the framework is meant as a guide that structures the search and match thought process we follow when we look for evidence in data of the thin market mechanism. Let the number of bidders $N_{h,t}$ for a housing auction of unit h at time t be Poisson distributed, $N_{h,t} \sim \text{Poisson}(\mu_{h,t})$, in which $\mu_{h,t}$ is the expected number of bidders for unit h at time t. For simplicity, let $\mu_{h,t} = \mu$ be common to all auctions for units of similar type across time. The probability that an auction of unit h draws k bidders is given by:

$$Prob(N = k) = \frac{e^{-\mu}\mu^k}{k!}. \tag{10}$$

Let bidder b be among the k bidders. Bidder b has preferences F_b and considers the housing consumption utility $u(M_{b,h})$ he may extract from a match $M_{b,h} = m(F_b, AT_h)$ with house h with attributes AT_h. For simplicity, but with no loss of generality, we classify match-quality into three types, high, medium, or low:

$$M_{b,h} = \begin{cases} H, & m(F_b, AT_h) \geq m_H \\ M, & m_L < m(F_b, AT_h) \leq m_H, \\ L, & \text{otherwise,} \end{cases} \tag{11}$$

in which $m(F_b, AT_h)$ is a match-quality function.

Let bidder b have an income I_b, drawn from a general income distribution, and home equity E_b, drawn from a general equity distribution. Bidder b forms his willigness-to-pay (WTP) for a unit h on the basis of a utility-maximization over the utility stream from house h and other consumption. In this utility-maximization, bidder b optimizes what match-quality he may derive from unit h, $M_{b,h}$, by comparing the possible match-quality of other units and the utility from the consumption other goods while heeding his financial budget constraint imposed by his income I_b and equity E_b:

$$WTP_{b,h} = w(M_{b,h}, I_b, E_b), \tag{12}$$

in which the function w(.) incorporates access to credit and bank LTV-regulations.[4] The function w(.) is increasing in all three arguments. For us to illuminate on the thin

[4]In Norway, the financial authorities ask that banks limit credit to five times income and require 15 percent equity; with the possibility of waivers in certain cases after a "speed-limit" enforced by the authorities.

market mechanism the income and equity constraint are inessential, but we include them for completeness and because they will be involved in the stressed seller mechanism below.

Given the supply of houses for sale at time t, S_t, and the number of buyers on the market, B_t, the probabilities of good, medium, and low matches are $\rho_{G,t}(S_t, B_t), \rho_{M,t}(S_t, B_t)$ and $\rho_{L,t}(S_t, B_t)$ such that $\sum_j \rho_{j,t}(S_t, B_t) = 1$, j = G, M, and L. We assume that the probabilities are time-invariant, $\rho_{j,t}(S_t, B_t) = \rho_j(S_t, B_t)$, j = G, M, and L, even if the numbers of sellers S_t and buyers B_t are not. The number of bidders $N_{h,t}$ for unit h consists of these three types, thus $N_{G,h,t} + N_{M,h,t} + N_{L,h,t} = N_{h,t}$. The expected number of good matches is $E(N_{G,h,t}(S, B)) = \rho_{T,t}(S, B)E(N_h(S_t, B_t))$. Thus, the number of expected good matches $E(N_{G,h,t})$ is increasing in the expected number of bidders $E(N_{h,t})$:

$$\frac{\partial E(N_{G,h,t})}{\partial E(N_{h,t})} = \rho_G(S_t, B_t) \geq 0. \tag{13}$$

This is an essential result. The expected number of good match-bidders falls when the numbers of bidders fall. In thin markets, when the number of bidders fall, the number of good match-bidders fall. Thus, in thin markets, we expect a reduced number of bids that classify as an acceptable bid to the seller.

Let the seller's reservation price of unit h be $R_{h,t}$. Here, we may assume that the reservation price is time-invariant so $R_h h, t = R_h$, but below we shall see that we change this assumption when we invoke the impatient seller hypothesis. The sell price for unit h becomes equal to the second highest WTP across $WTP_{b,h}$ for the number of bidders $N_{h,t}$ when $N_{h,t} \leq 2$ as long as the second highest WTP is above the reservation price R_h. When only one willingness-to-pay among bidders b, $WTP_{b,h}$, is above the reservation price R_h, the sell price $P_{h,t}$ becomes the reservation price:

$$P_{h,t} = \begin{cases} \pi_h = max_{-1,b}(WTP_{b,h}), & N_{h,t} \geq 2, max_{-1,b}(WTP_{b,h}) \geq R_h \\ R_h, & max_b(WTP_{b,h}) \geq R_h, max_{-1,b}(WTP_{b,h}) < R_h \\ \text{no transaction}, & \text{otherwise}, \end{cases} \tag{14}$$

in which there is no subscript t on π_h because there are no subscripts t on the WTPs here and the notation $max_{-1,b}(WTP_{b,h})$ denotes the second highest WTP for unit h among bidders b when the number of bidders is at least two. Since π_h is at least as high as the reservation price, the transaction price $P_{h,t}$ is non-decreasing in number of bidders $N_{h,t}$. To see this, keep in mind that an increase in $N_{h,t}$ in expectation is associated with an increase in the number of good matches, $N_{G,,h,t}$. When there is one good match, and the willingness to pay for the bidder with this match is above the reservation price, the sell price becomes equal to the reservation price. When there are two good matches, and the WTP for these bidders are above the reservation price, the sell price becomes the second highest willingness-to-pay.

As in Anundsen and Røed Larsen (2018), the probability that the number of good matches, given $N_{h,t}$, is equal to n follows a binomial distribution. Since the highest price π_h requires at least two good matches, the probability that that the sell price is equal to the highest price, $P_{h,t} = \pi_h$, is the sum of probabilities that the number of good matches is equal to two or more. Following Anundsen and Røed Larsen, we then see that the probability of a high price $Prob(P_{h,t} = \pi_h)$ is increasing in the number of bidders $N_{h,t}$, $\frac{\partial Prob(P_{h,t}=\pi_h)}{\partial N_{h,t}} > 0$. Thus, a higher number of bidders is associated with an increase in the frequency of high prices.

Nenov, Røed Larsen, and Sommervoll (2016) show that December is month of low activity in Norway. The implication is that sell prices should be lower in December, everything else being the same, due to thin market effects.[5] Below, we study bidders in auctions and

[5]A more advanced framework is required to study and separate the outcomes of different relative magni-

advertisements in order to investigate further the activity on the demand and supply sides and whether data support the thin market effect as a generating mechanism.

5.2 Optimum waiting time and discounts

While the thin market mechanism involves the market as an explanation, another possibility is the seller himself. If the seller is forced to deviate from his optimization plan, he might not be able to obtain the sell price he otherwise could have. We shall outline our thinking in a simple framework. Let the willingness-to-pay for a given unit, $WTP_{b,h}$ for a given unit h have distribution across buyers b described by a density function $D_{h,b}$. When the seller of the housing unit h has a reservation price R_h within the range of the WTPs across buyers b, i.e. $min_b(D_{h,b}) \leq R_h \leq max_b(D_{h,b})$ there is a non-zero, but non-unity, probability that a transaction will take place. There might be a meeting and a match between the buyer and the seller.

Optimizing sellers with the reservation price R_h essentially attempt to solve an optimum stopping problem. They know that the arrival rate of bidders is stochastic, and that an increase in the number of auctions affects the probability of a sale and a high sell price. Sellers balance the benefits from arranging one extra auction with the cost of arranging one. There is a growing literature on challenges involving holding time, ask prices, and sell prices. For example, Anglin, Rutherford, and Spring (2003) study the relationship between ask price and time-on-market, and show that higher ask price implies longer expected TOM. Anglin and Wiebe (2013) demonstrate that sellers affect sell price through ask price.

The cost is observable for a buy-first-then-sell moving owner-occupier. This owner services two mortgages in the period he owns two units. For a sell-first-then-buy mover, the cost includes the lost utility of postponing moving house, the utility loss from potentially losing out on a prospective house, the lost capital gain of not owning in the transition period,

tudes in the two effects that follow from i) a reduced number of sellers and ii) a reduced number of buyers. It is fathomable that the number of sellers fall much more than the number of buyers so that the remaining buyers compete over very few units.

and the cost of renting an interim unit between selling and buying. In the shortest notation this utility optimization problem can be written as:

$$v_h(t) = max_t \quad B_h(t) - C_h(t) \qquad given \qquad f(B_h(t), C_h(t), V_h(t)) = 0, \tag{15}$$

in which v is the utility resulting from the solution to the optimization problem of seller h, B represents the benefits of waiting, C represents the costs of waiting, t is time-on-market, f is a non-specified function, and V is a non-negative individual parameter reflecting preferences and financial position. We think of V as being allowed to vary across time for a given individual. Waiting costs increase with time-on-market, thus $\partial C_h(t)/\partial t > 0$. Expected benefits increase with the probability of being able to find a bidder with a high-utility match, thus $\partial B_h(t)/\partial t > 0$.

The seller searches for the optimum waiting time t^O. The stressed or impatient seller mechanism implies that the problem becomes a constrained problem with changes in V. We suggest that there would be different empirical traces resulting from a) no changes in $V_h(t)$, b) a monotonic time transformation of $V_h(t)$ (growing impatience), or c) a discontinuity in $V_h(t)$ (a bank-imposed deadline). We inspect the time-development of the sell-appraisal spread, TOM, and the survival rate.

6 Empirical evidence of generating mechanisms: Thin markets, stressed sellers, or impatient sellers

6.1 Thin markets

Table 6 reports the results from regressing our measure of price seasonality, PS, on our measure of transaction volume seasonality, VS, and our measure of horizontal differentiation. Regression I of price seasonality on transaction volume seasonality yields a highly statistically significant estimate coefficient of 0.131. The interpretation is that a unity increase in a housing market segment's transaction volume measure is associated with a 0.13 increase in that segment's price seasonality measure. The adjusted R-square is 0.4, supporting a claim of an association between price seasonality and volume seasonality, although we interpret the explanatory power with caution since both independent and dependent variables are constructed.

In regression II, we regress the price seasonality measure on the measure of horizontal differentiation. The estimated coefficient is 0.316 and highly statistically significant. The results indicate that a unity increase in the horizontal differentiation measure is associated with an increase of almost one third in the price seasonality measure, clearly supporting the idea that markets characterized by horizontal differentiation has more price variation with seasons across the year. In regression III, we observe that the explanatory power does not increase, but the estimate of the VS-measure coefficient becomes larger while the estimate of the HD-measure coefficient becomes negative. This is because the VS-measure and the HD-measures are closely related.

These results demonstrate that across segments there is an association between price seasonality, i.e. large December discount, and volume seasonality, i.e. large reduction in transaction volumes in December. In light of our interpretative framework described above, one generating mechanism of the December discount appears to be that fewer sellers and fewer buyers are in the market so fewer good matches between buyer preferences and unit attributes occur.

Table 6. Regressions of price seasonality on transaction volume seasonality and horizontal differentiation. Norwegian segments of municipality, type, size. 2002-2013

	PS		
	I (on VS)	II (on HD)	III (on VS + HD)
VS	0.131 (0.011)		0.174 (0.039)
HD		0.316 (0.027)	-0.118 (0.098)
No. segments	230	231	230
No. units		449,719*	
Adj. R-sq.	0.401	0.331	0.403

Notes: *3,214 observations from the year 2014 are not used since 2014 does not cover the whole year. Standard errors are White heteroskedasticity-consistent ones, computed using the R routine vcovHC() in the lmtest-package. Horizontal differentiation is 1-Adj. R-square from a log-linear regression of log(sell) onto a space spanning attributes, construction year, and time fixed effects. The smaller the adjusted R-square the higher the horizontal differentiation. The hedonic regression that produces the adjusted R-square for each sub-segment is log(sell) on log(size), squared(log(size)), three dummies for construction year period, years since 2000 (year trend line), and eleven month dummies.

6.2 The stressed seller effect

If there is a discontinuity in financing conditions, e.g. if the bank's interim loan has an expiration date, or if sellers perceive that there is a discontinuity in urgency, we expect to find traces of such discontinuities in metrics such as the sell-ask spread, the sell-appraisal spread, and the survival rates for units announced for sale in August and September. This idea is grounded in our framework outlined above: If an optimizer faces a new constraint, the optimal solution might not be obtainable. Below, we discuss the results from a non-parametric local regression of sell-appraisal spreads across days after registration while comparing cohorts of monthly units. The rationale is that a discontinuity caused by a stressed seller effect can only explain the December discount if it does not exist in other monthly cohorts.

Table 7 tabulates results from regressions of sell-ask and sell-appraisal spreads onto a list of regressors. In the most parsimonious model, model I, the list includes size of the unit, days since 1 August, and the interaction variable December dummy multiplied by days since 1 August. The hypothesis of stressed sellers implies a statistically significant estimate of the coefficient of the interaction variable and that it is negative. Although we find a statistically significant estimate, it is positive. The interpretation is that the declining spread continues into December, but with a reduced slope, not larger slope. This is the opposite of the stressed-seller implication. The table shows predicted sell-ask spreads of 21 November, 1 December, and 11 December of, respectively, - 1.9, -2.8, and -3.6 percent for model I and predicted sell-appraisal spreads of, respectively, -5.4, -6.5, and -7.6 percent for model III.

This evidence does not support the hypothesis of a stressed seller effect that is activated in December. However, the time development in the predicted spreads appear to indicate that these spreads are monotonically decreasing functions of time, suggesting a growing impatience. In the next sub-section, we pursue this possibility.

Table 7. Sell-ask/sell-appraisal spread on regressors

Dependent variable	Sell-ask		Sell-appraisal
	I	II	III
Intercept	9.78e-2 (9.3e-4)	8.60e-2 (2.1e-3)	9.69e-2 (2.1e-3)
Size	-1.68e-4 (5.8e-6)	-5.24e-5 (1.1e-5)	-1.24e-4 (9.4e-6)
Appraisal		-3.45e-9 (3.8e-10)	
Type FE		YES	
Sale Year FE		YES	
City FE		YES	
Construction Year FE		YES	
Days since 1 Aug	-1.06e-3 (1.2e-5)	-1.01e-3 (1.2e-5)	-1.24e-3 (1.4e-5)
Dec*Days since 1 Aug	1.73e-4 (1.5e-5)	1.70e-4 (1.5e-5)	1.52e-4 (1.9e-5)
Sell months in sample		Aug-Dec	
Announced for sale		Aug-Sep	
N	56,413	56,033	
Adj. R2	0.134	0.160	0.170
Predicted spread 21 Nov	-0.019		-0.054
Predicted spread 1 Dec	-0.028		-0.065
Predicted spread 11 Dec	-0.036		-0.076

Notes: The spreads are the difference between sell price and ask price as a fraction of ask price and between sell price and appraisal value as a fraction of appraisal value. White HC-standard errors for model I-II, classical for sell-appraisal. Truncation on TOM <153, announced for sale in August and September and transacted in August-December. Predicted spreads for detached house in Oslo, size 100 sq.m., built after 2000, transaction year 2012

6.3 Sell-appraisal spreads for monthly cohorts

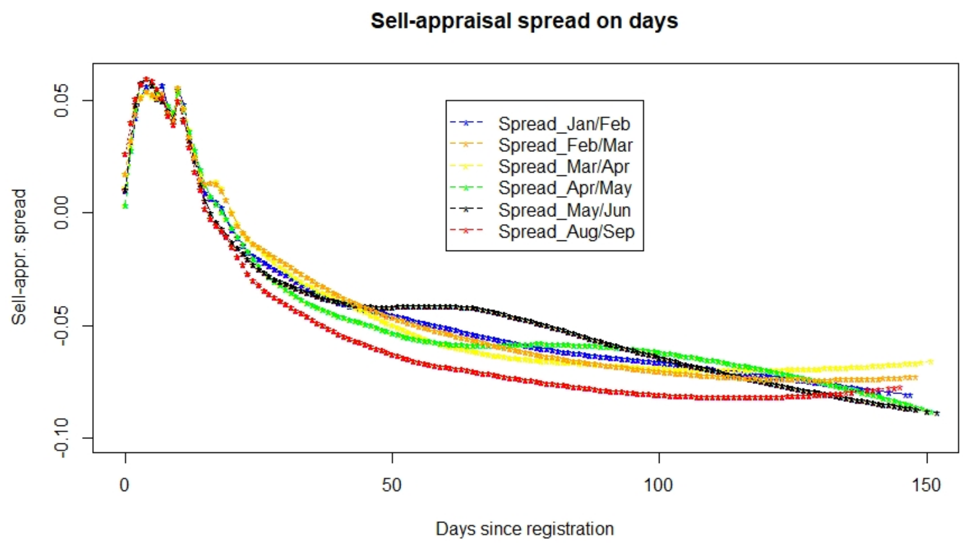
The results of the regressions in Table 7 are consistent with an increasing Fall trend of impatience. If this impatience manifests itself more in the Fall than in the Spring we should detect it when we compare the sell-appraisal spreads for units that were put on the market in different seasons. Figure 1 plots the local regression-smoothed spread as a function of days since the advertisement was announced online. The plot includes the sell-appraisal spreads for units of different cohorts. We partition transactions into two-monthly cohorts using the advertisement date.

We first observe that the spread increases the first few days after the advertisement has been registered online. This is a result of the institutional setting. Most units are announced for sale at least a week before the public showing, after which the auction starts.[6] Sell prices are typically at their highest right after the public showing (Røed Larsen (2019)), i.e. between 8 and 10 days after the advertisement announcement, due to a self-sorting mechanism in which units with multiple good matches follow a different auction process than units with few good matches.

There appears to be no difference between the cohorts during the first two weeks of days since the registration of the advertisement. When the number of days since registration increases the spreads tend to fall. For units put up for sale in August and September (the red line) this reduction in the spread is stronger than for any Spring cohort although the spreads converge at the end point. This pattern supports both the notion of thin markets and the notion of an increased impatience during the Fall months, but not a stressed seller hypothesis.

[6] Bids may be extended to the seller before the auction, but then the realtor cannot be the mediator.

Figure 1. Sell-appraisal spreads by days since advertisement registration. Local regression. Monthly cohorts

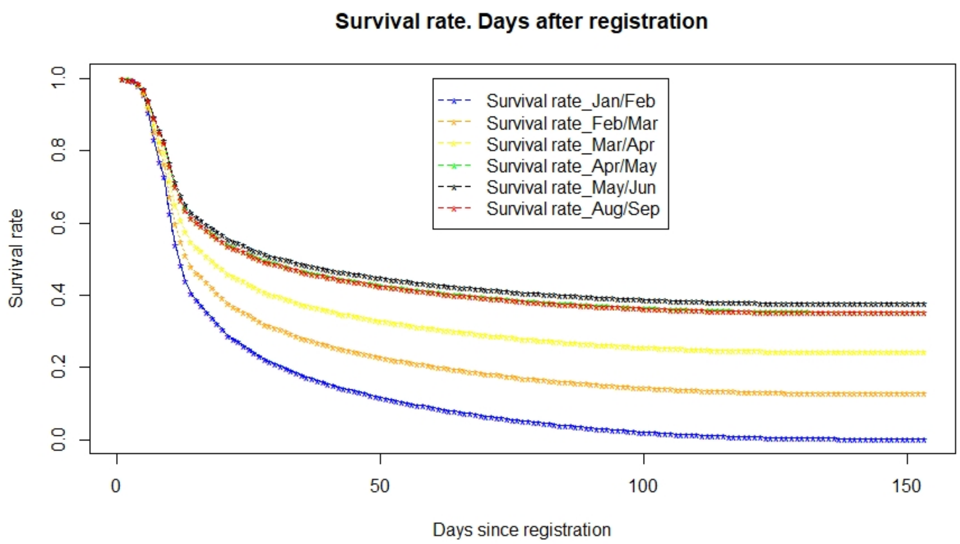


Note: The Jan/Feb-cohort was constructed by including units put up for sale (advertisement registration date) in January or February and sold between January and May. We restrict TOM to be equal or less than 153 days. The other cohorts are constructed similarly, one month later. The plot shows the predicted spread using the local regression function "loess" in R with a smoothing parameter of 0.2.

6.4 Survival rates of monthly cohorts

In Figure 2, we plot the survival rates for the two-monthly cohorts. The survival rates are the share of unsold units out of all units put up for sale measured for each day since the date of advertisement registration. The August-September cohort is among the flattest while the January-February cohort is among the steepest. Since survival rates may be different in different regional markets, we include in the Appendix Figure A1 for Oslo. For Oslo, the August-September cohort is clearly the flattest. The plotted survival rates are consistent with the impatient seller effect since sellers who have not yet sold after a substantial number of days on the market tend to get impatient. It appears this effect is stronger during the Fall months. The pattern in survival rates is also consistent with fewer buyers, but also indicates a higher rates of surviving sellers. Survival rates alone are inconclusive as to whether or not the total effect is fewer sellers overall. Below, we discuss the activity of new sellers entering the market in the Fall months.

Figure 2. Survival rates by days since advertisement registration. Monthly cohorts. Monthly cohorts



Note: The Jan/Feb-cohort was constructed by including units put up for sale (advertisement registration date) in January or February and sold between January and May. We restrict TOM to be equal or less than 153 days. The other cohorts are constructed similarly, one month later.

6.5 Impatient seller metrics

The cross-sectional regressions of price seasonality on volume seasonality and the heterogeneity measure indicate the existence of a thin market effect. The evidence in Table 7 and Figures 1 and 2 are consistent with thin market effects. Although the results in Table 7 and Figures 1 and 2 also could be caused by an impatient seller effect, it is possible that all the results above are solely due to a thin market effect. We seek evidence that single out an impatience effect.

In order to find evidence that strongly suggest an impatient seller effect, we have investigated the development of auctions, bid-for-bid, in different months. We have looked for evidence of possible changes in seller's reservation price. Although the reservation price is unobservable, the rejection of a bid is observable. A rejection of a bid uncovers a lower limit of the latent reservation price. In Table 8, we present results from regressions using two metrics of impatience estimated on bid-by-bid auction data from the realtor arm, DNB Eiendom, of Norway's largest bank, DNB.

Our two metrics of impatience comprise: i) The percentage difference between the accepted bid and the highest declined bid given that the seller declined it more than 7 days prior to the date of the accepted bid and ii) The number of days from the highest declined bid to the date on which a bid was accepted. We ran four regressions, two for each metric. The first regression of each metric uses only month dummies while the second regression includes controls. In column two, we see that the estimated coefficient of the December dummy is -1.25 and statistically significant. It is larger in absolute value than the estimated coefficients of November, October, and September. It is much larger than the estimated August coefficient of -0.52. The interpretation is that a December sale reduces the difference between the sell price and the highest declined bid. This reduction takes place in all Fall months, at increasing strength, and supports the notion of growing impatience as the holiday season nears.

In column four, we see that the estimated December dummy coefficient is -78 and statistically significant. It is higher in absolute value than the estimated coefficients for other Fall months. All estimates of Fall month dummy coefficients are negative and become more negative during the Fall months. Again, the impatience metric appears to display increasing strength during Fall. In fact, the estimated coefficients both of column are and column four are monotonically falling with time. This supports a notion of growing impatience.

Table 8. Impatience in December

	Diff. acc. decl.	Diff. acc. decl.	Days b/w acc. decl.	Days b/w acc. decl.
August	-0.340	-0.524	-4.701	14.447
	(0.226)	(0.346)	(17.020)	(20.134)
September	-0.742***	-0.913***	-57.711***	-34.518*
	(0.222)	(0.334)	(16.538)	(19.466)
October	-0.967***	-1.090***	-72.591***	-47.746**
	(0.222)	(0.337)	(16.617)	(19.587)
November	-0.788***	-1.193***	-57.482***	-58.016***
	(0.229)	(0.343)	(16.967)	(19.978)
December	-0.895***	-1.248***	-88.046***	-78.179***
	(0.264)	(0.393)	(19.347)	(22.873)
Days since decline		-0.000**		
		(0.000)		
TOM		-0.006***		0.230***
		(0.001)		(0.049)
N	25,568	12,445	20,792	12,445
R2	0.00208	0.180	0.00260	0.155
Controls		✓		✓
House type FE		✓		✓
Zip-code FE		✓		✓
Year FE		✓		✓
Realtor FE		✓		✓

Notes: We implement the following conditions. We require observed sell price, ask price, and size. We compute the first and 99th percentiles of size, appraisal value, ask price, and sell price. We trim by removing observations at least one variable outside the 1st-99th percentile interval. We remove observations when the difference between accepted and declined bid was outside the +/- 30 percent interval. Control variables are log(size), squared log(size), time-on-market, year, zip code, house type, realtor identification, realtor branch, and the other months.

7 Discussion

In order to explore further the underlying activity of demand and the supply, we study inspect the bid-for-bid auction dynamics in more detail and the temporal aspect of putting a unit up for sale. In particular, we examine:

- The demand side: The number of auctions, bidders, bids, and bids per bidder

- The supply side: The number of new units put up for sale

7.1 The demand side: bid-for-bid auction data

Table 9 presents results from multiple metrics for selected months from our auction data set: number of auctions, mean number of interested individuals, mean numer of bidders per auction, mean number of bids per auction, mean number of bids per bidder, frequency of contested auctions, and mean difference of accepted bid and highest declined bid.

We observe that on all metrics, the December metric scores low or lowest. The most easily-detected is the number of auctions. It is 1,554 for detached units and 2,313 for apartments in contrast to 3,669 and 5,338, respectively for November. In August, the metrics are 4,121 and 6,180. Clearly, the demand side activity is strongly reduced in December.

This activity reduction also leads to less contested auctions, as defined as auctions with at least three bidders with at least three bids. 4.83 percent of auctions of detached houses were contested while 6.61 percent of apartments were. These metrics are clearly lower than in other Fall months. While mean number of bid per auction for December is 5.57 for detached houses and 5.99 for apartments, they are above 6 for all other months.

Table 9. Auction metrics, by month

Month	No. auc.	No. int.	No. bidders	No. bids	Bids per bidder	Perc. contested	Diff. acc. decl.
Detached:							
January-July	24996	8.47	2.14	6.34	2.86	6.97	5.81
August	4121	8.60	2.16	6.34	2.81	7.55	6.07
September	4901	8.58	2.09	6.24	2.87	6.65	5.71
October	4384	8.51	2.04	6.06	2.87	6.39	5.05
November	3669	8.16	2.06	6.21	2.94	6.62	5.76
December	1554	8.27	1.92	5.57	2.86	4.83	5.13
Apartments:							
January-July	38257	6.70	2.28	6.52	2.76	8.57	5.45
August	6180	6.73	2.27	6.52	2.75	8.38	5.44
September	6500	6.55	2.17	6.27	2.78	7.60	4.58
October	6042	6.34	2.12	6.09	2.78	7.15	4.32
November	5338	6.60	2.16	6.32	2.82	7.47	4.75
December	2313	6.67	2.10	5.99	2.80	6.61	4.88
All							
January-July	73694	7.37	2.22	6.47	2.81	7.95	5.58
August	11871	7.53	2.23	6.52	2.80	8.17	5.67
September	13236	7.41	2.13	6.27	2.83	7.18	5.08
October	12229	7.24	2.09	6.14	2.84	6.93	4.67
November	10461	7.14	2.10	6.22	2.87	6.86	4.99
December	4495	7.31	2.03	5.83	2.82	5.98	4.84

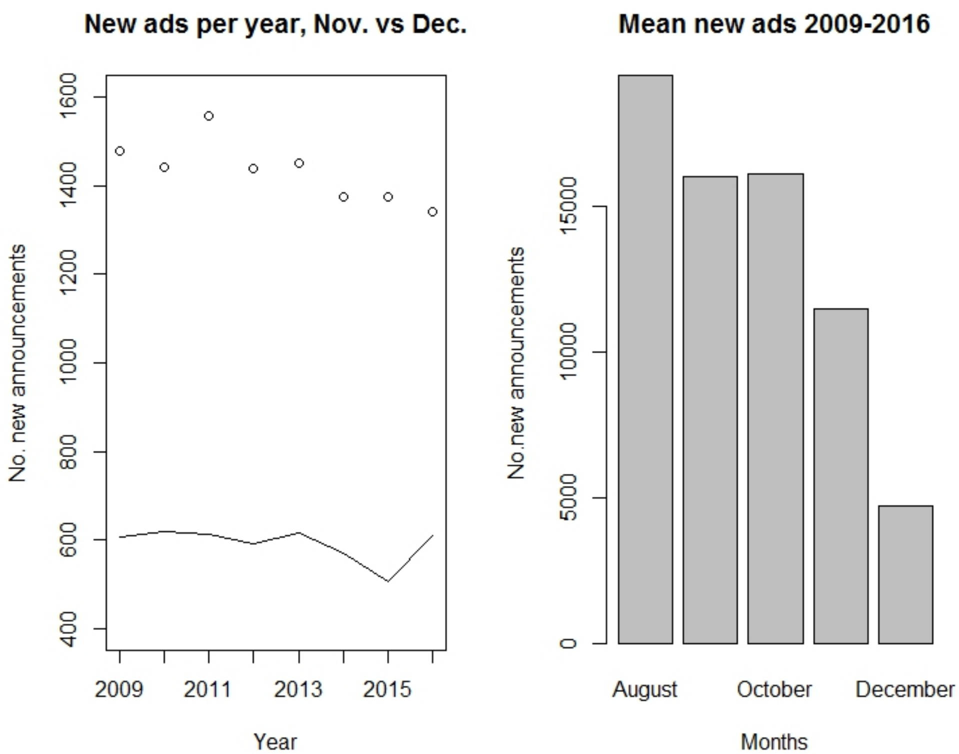
Notes: We define contested auctions as auctions in which three or more bidders extend three or more bids each. The variable "Diff. acc. decl." refers to the mean percentage difference between the accepted bid and the highest declined bid.

7.2 The supply side: advertisement data

Using the advertisement data, we study the number of new advertisements on the on-line platform *Finn.no* as a measure of the supply side activity. We seek to examine the tendency to entry into the market in December. Figure 3 plots new for-sale announcements in the period 2009-2016. The left-hand-side panel plots new advertisements for each year in the period 2009-2016 for November and December. We see that the November announcements (dots) are consistently much higher than December announcements (line).

The right-hand-side panel plots the mean number of new advertisements for the whole period 2009-2016 for each months August-December. Over the period, in December 4,733 new for-sale announcements were made compared to 14,250 per month for the rest of the year. In comparison, November-announcements consist of 11,461 units, which is less than the typical month, but much more than in December.

Figure 3. New advertisements per year, November vs December, and mean new ads 2009-2016. Oslo



Note: November = points, December = line.

7.3 Why do temporally thin markets exist?

This article finds that a unit tends to sell at a lower sell price in December, controlled for unit and seller heterogeneity. The evidence supports the notion that the December discount is rooted in a thin market mechanism and an impatient seller effect rather than a stressed seller effect.

One question is why the housing market is characterized by temporally thin markets? This synchronization of buyer and seller activity is commented upon by Nenov, Røed Larsen, and Sommervoll (2016), and they document the existence of thin and thick markets. One obvious answer is that thin markets are a necessary side-effect of thick markets. When markets are thick in some months they must be thin in others. But this is not answering the question; only a reformulation of it. Why do thick markets exist and how do they arise? Instead of answering the "why", we can at least say that thick markets facilitate good matches. How they arise is a challenging question that we leave for future research.

This article may nevertheless give a hint at where to search. It appears that markets become thinner and sellers more impatient as the holiday season nears. Thus, future research can explore deeper what causes the activity to slow-down. Physical variables such as temperatures and sunlight are not good candidates as our Figures 1 and 2 show that January and February are months with high sell-appraisal spreads and steeply falling survival rates, indicative of good matches and high activity. January and February are colder months than November and December and equally dark. It seems more likely that thin markets and low activity are related to societal factors and calendar effects.

8 Conclusion and policy implications

This article studies the December discount. Realtors have reported for some time that house prices tend to be lower in December than in other months. We document that this is indeed the case. we then rule out that a composition effect can explain all of the December discount. A fully specified hedonic model yields statistically significant estimates of a December effect.

We control for unobserved unit and seller heterogeneity using a battery of techniques. We use repeat-sales to control for permanent unit effects. We use ask price to account for temporary units effects. We use an instrument variable approach that involves appraisal value to control for seller effects. We also study units put up for sale in August and September, in contrast to units put up for sale in November and December, in order to further control for unobserved heterogeneity. To take into account time-on-market effects arising from August and September units remaining on the market until December, we compare sell-appraisal spreads with other months with equally long time-on-market.

Our results indicate that the December discount is at least one percent. We find supporting evidence for a thin market effect and an impatient seller effect, but we do not find support for a stressed seller effect. The thin market evidence is found using cross-sectional data on 231 sub-markets. The more seasonality in volume the more seasonality in prices. The impatient seller effect is documented through bid-by-bid data from auctions. We study auctions in which the seller has declined a bid at least seven days ago and then accept a bid. We suggest the rejection of a bid is a lower limit of a reservation price. When the difference between an accepted bid and a declined bid shrinks this may indicate a change in the reservation price and thus be thought of as an impatience gauge. The mean difference falls throught Fall and is at its lowest in December.

Since the December discount is at least one percent of the price of a house, and since part of this appears to be linked to think markets and sub-optimal matching, it shows there may be substantial welfare gains to be made by making sure housing markets are arranged to ensure optimal matching between buyers and units. Matching a household's preferences with a housing unit's attributes in a efficacious way allow welfare gains. This means that policy makers can take these results to make a two-fold wish-list: a) construct institutions that make housing markets enjoy thick-market benefits and b) employ policies that help households locate matching houses in a match-efficient way. Sellers and buyers may also take notice. Sellers would be advised to avoid the thin markets in December, but buyers would expect to compete with fewer competitors. The caveat for buyers is that the probability of a good match between preferences and attributes is lower in thin markets.

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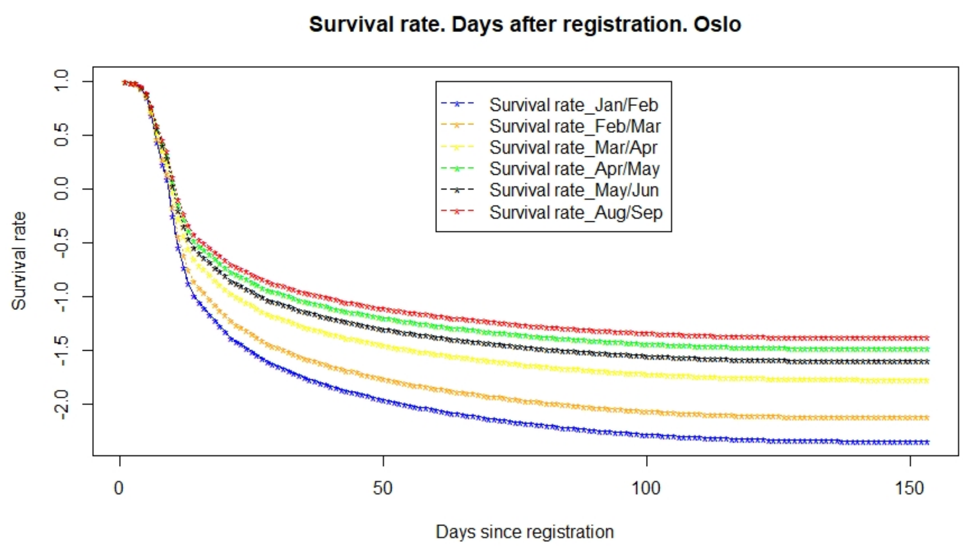
Appendix

Figure A1. Survival rates by days since advertisement registration. Monthly cohorts, Oslo



Note: The Jan/Feb-cohort was constructed by including units put up for sale (advertisement registration date) in January or February and sold between January and May. We restrict TOM to be equal or less than 153 days. The other cohorts are constructed similarly, one month later.