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House price seasonality, market activity, and the December discount

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Abstract

In Norway, house prices tend to drop in December. This regularity is persistent across regions and over time. I exploit a transaction data set with high temporal granularity to document and estimate the size of the December discount. I control for a composition effect using a hedonic model and I control for unobserved heterogeneity by using repeat sales and involving ask prices and appraisal values. By segmenting into submarkets, I search for determinants of price seasonality. The evidence suggests that the December effect is linked to time-on-market for each unit and transaction volumes within each submarkets.

KEYWORDS

December discount, housing market, seasonality, time-on-market, transaction volume

1 | INTRODUCTION

In Norway, mean house prices fall in December. At first blush, one would expect that this price pattern would encourage people to buy in December and discourage people from selling in December. Since the December discount could be exploited or avoided, we would expect it to gradually disappear. The fact that a pattern of predictable price seasonality exists begs scrutiny. In the words of Ngai and Tenreyro (2014): "The predictability and size of seasonal fluctuations in house prices pose a challenge to existing models of the housing market." One trivial explanation would be that units sold in December simply are different from units sold in September. If such a composition effect accounts for the whole difference, the price drop is no discount nor is there any special buying opportunity or discouragement from selling. Then, the explanation is that the transacted units are different in December. If the composition effect consists of transactions of different unit types or different residential locations, the composition effect would be seen in and handled by a hedonic model. Another, more challenging, possibility is that units sold in December could be of lower quality. Such unobserved heterogeneity would bias the discount estimates since it then would be caused by latent quality features that would not be included in the list of observable attributes. This article suggests using ask prices and appraisal values to account for unobserved heterogeneity, and asks one key question: Is the December price reduction a discount for a given quality?

The answer is "yes." We do observe a quality-controlled price reduction in December, and its magnitude is about 1.3–1.5% when sell prices are compared to sell prices in September. We care about the precision of this estimate because seasonal house price fluctuations are economically interesting (Ngai & Tenreyro, 2014). This interest in house price seasonality has a long history, as has the study of the mechanisms that cause price periodicities. For example, Harding, Rosenthal et al. (2003) show that bargaining power among families with school-age children is lower during the summer compared to during the school year. They also demonstrate that variables outside of the hedonic model can, and indeed do, have important effects on house prices. It thus matters whether the December decline is sufficiently small that it can be ignored or large enough that its presence presents a puzzle.

The main challenge researchers face when they attempt to estimate seasonality in prices is unobserved heterogeneity among the housing units. It is plausible, perhaps even probable, that different kinds of units sell at different periods of the year. However, time-invariant characteristics can be handled by using repeat-sales data. Thus, the more difficult challenge is unobserved unit heterogeneity in time-varying variables, which may or may not be large. Since it is an empirical question whether time-varying omitted variables may cause a bias in repeat-sales indices, this article develops and employs an identification strategy for how to utilize ask prices and appraisal values in order to control for time-varying heterogeneity. The importance of having a strategy for controlling for heterogeneity was seen in Donner et al. (2016), who sought to estimate whether forced sales truly involved lower sell prices, and they pointed to Clauretie and Daneshvary (2009) who stated the need for a differentiation between the foreclosure status and attributes of the unit. Similarly, in seasonality studies it is adamant to differentiate between calendar effects and characteristics effects since it is possible that lower-quality units are off-loaded at the end of the year. In fact, Zhou (2015) find that when a large discount is observed it is often linked to property condition.

The novelty of this study lies in extracting information from a data set with exact list and sell dates and ask prices and appraisal values. My contribution is empirical and extend the seasonality study by Ngai and Tenreyro (2014) along three dimensions. First, while they focus attention on two 6-month periods, this article's granular data allow the construction of a monthly price grid. Using this finer resolution, this article shows that there are price patterns between months, that is, regularities with shorter span than half-years. Second, using data on ask prices and appraisal values, this article can control for unobserved heterogeneity, which in turn allows us to alleviate a possible bias in the repeat-sales index (Bourassa et al., 2013). Third, I use the richness of my data to probe into the connection between time-on-market (TOM) and temporal price patterns.

Specifically, while Ngai and Tenreyro use a repeat-sales index, this article uses a repeat-sales setup augmented with ask prices and appraisal values and argues that this additional information is essential to make sure there is no unobserved heterogeneity underlying price seasonality estimates. The ask price, after all, reflects the market value set by the person who knows the most about the unit, namely, the seller. The appraisal value is an assessment gauge set by a professional appraiser. It is exogenous to the seller, and is a valuable source of information if we worry that the ask price may be set strategically (see, e.g., Anglin et al., 2003; Anglin & Wiebe, 2013; Anundsen et al., 2022). The hedonic model of log sell prices implies a 5% price drop between September and December prices. While the unit fixed effect model of log sell price implies only a small difference, the unit fixed effect model of log sell price that controls for unobserved heterogeneity using ask price, yields a difference of 1.3%. Using appraisal values, we find a September–December price difference of 1.5%. Thus, it seems warranted to seek to control for time-varying unit effects.

Having established the existence of a December discount, this article looks at mechanisms that may cause this price pattern. One candidate is seller motivation. It is possible that two identical units sell at two different prices in September and December if a nonsuccessful seller becomes more motivated to off-load the unit before year's end. Campbell et al. (2011) point to idiosyncratic factors such as urgency in their study of forced sales and urgency might affect the relative bargaining position between sellers and buyers (Harding, Knight et al., 2003; Harding, Rosenthal et al., 2003). Thus, since urgency is linked to TOM, an essential variable in any attempt to look at the interplay between unit types, transaction volumes, and price periodicities is TOM (Carillo & Pope, 2012; Carillo & Williams, 2019). While this article cannot establish causality, it nevertheless explores the role TOM plays in the December discount. It shows that the transaction volume in December is a third of the volume in September. While TOM in September is 39.1 days, it is 55.2 days in December. These statistics may give future research clues as to what we should look for when we seek to map out factors that are determinants of temporal price patterns.

In fact, Carillo and Pope (2012) demonstrate that the distribution of TOM is time-varying, which is a necessary condition for it to be linked to price patterns. They also ask whether certain units could be harder to sell than others so that there would be longer TOMs for certain units. If so, one would be tempted to infer that such homes could lie at the root of a December discount. This article controls for unit fixed effects in the discount estimation and also use a repeat-TOM setup (Carillo & Williams, 2019) to demonstrate that TOM, however, is not connected to the unit. Rather, TOMs are mean-reverting. However, this finding hints at another possibility, namely, a stochastic process that implies that units may stay on the market for a long time during Fall. That possibility is consistent with another finding in this article: The survival rate (i.e., the rate at which units remain unsold) is higher for listings in all Fall months compared to January.

This article uses two approaches when it tries to link TOM and market activity to price seasonality. First, in a micro-based approach, I study TOMs and sell prices for repeat sales. When segmenting the data based on TOM, the estimated December coefficient becomes similar to coefficients of September and October within the segments, indicating that TOM is part of the story. Again, TOM itself does not appear to be linked to the unit since a regression of the second TOM on the first TOM shows that TOM is mean-reverting and there is little persistence. Instead, when we estimate a repeat-TOM model with unit fixed effects, we observe that the same unit has substantially longer TOM when it is sold in December compared to other months. Second, in a macro-based approach, I estimate market characteristics of submarkets of houses and apartments in municipalities and show that there is an association between low market activity and the magnitude of the December discount.

This article's demonstration that there are persistent monthly price patterns should add to the growing literature on how the housing market works. Since the financial crisis, there has been a growing realization that the housing market is important to the macroeconomy and thus that it is advantageous to understand its mechanisms (Leamer, 2015). Any price regularity, be it weekly

(Røed Larsen, 2021), seasonally (Hattapoglu & Hoxha, 2021; Ngai & Tenreyro, 2014), or cyclically (Leamer, 2007) should be of interest. After all, what moves the housing market has the potential to have real economic consequences, which is one of the reasons why forecastability of house prices has been of long-standing interest to economists and policymakers (Case & Shiller, 1989; Røed Larsen & Weum, 2008). It is possible that the magnitudes of the effects are so small that they offer no profitable arbitrage activity (Rosenthal, 2006) or invite no policy concern, but, ultimately, this remains an empirical question.

Related literature

This article examines the empirical traces of the idea that temporal price patterns in house prices is related to temporal patterns in market activity. The basis for the idea can be found in search theory (see, e.g., Diaz & Jerez, 2013; Genesove & Han, 2012; Kashiwagi, 2014; Maury & Tripier, 2014, and Krainer, 2001). One key factor behind temporal price patterns appears to be the number of market participants, which influences the probabilities of different levels of match quality between buyer preferences and house attributes. In turn, the match qualities may affect realized prices (see Kaplanski & Levy, 2012; Nenov et al., 2016; Ngai & Tenreyro, 2014; Novy-Marx, 2009, and Anundsen & Røed Larsen, 2018).

Essentially, seasonality is a price pattern that shares periodicity with business cycles. While seasonality is linked to calendar effects and the business cycle pattern to economic fundamentals, the underlying thinking for understanding the pattern of a December discount could share features with Diaz & Jerez (2013). They note how there is a joint cyclical behavior of house prices, sales, and TOM. In principle, the 31 days of December is a miniature version of a downturn, and so their observation of a comovement of prices, sales, and TOM should be found in this article's temporal measures. However, it is also plausible that seasonality has different roots than cyclicality. The business cycle is not periodically reoccurring while seasonality is. This indicates that the determinants of house price seasonality may also be found in factors exogenous to the economy, such as the school calendar, weather, moving patterns, or the holiday season (Harding, Rosenthal et al., 2003).

The results in this article shed light on, and is consistent with, the model Albrecht et al. (2007) construct in which agents enter the market relaxed and becomes increasingly desperate to sell as TOM grows, and so the expected price falls with TOM. Sales with long TOM in December might have been the result of a one-on-one negotiation rather than an auction (Coles & Muthoo, 1998) even if the mean reversion of TOM implies that the long TOM is most likely the result of a random process. My results are less compatible with the idea proposed by Taylor (1999), in which TOM is a quality signal, in that I show that the second TOM of a given unit is more or less orthogonal to the first TOM of the same unit. When we segment on TOM, the estimated December effect is reduced. In other words, December units that sell with a TOM typical of September, do not experience a large discount. September units that sell with a TOM typical of December experience price discounts. It appears that it is the longer December TOM that is connected to the lower December prices and that these longer TOMs are generated by a process not linked to the unit itself.

This article is structured in the following way. Section 2 presents the data sources and gives a few details on the institutional background. Section 3 presents the identification strategy and goes through the empirical techniques I use. Section 4 contains empirical results. In Section 5, I explore what can explain the December discount and present evidence that suggests TOM and market activity are linked to the December discount, either as causal factors or as outcomes of the same underlying causes. Section 6 discusses a few ways to probe deeper into measures of market activity. Section 7 concludes and offers a few potential policy implications. In the Appendix, I have included additional tables and figures.

2 | DATA AND INSTITUTIONAL BACKGROUND

2.1 | Data source

From the collaboration with real estate agencies, the bank-owned data analytics firm *Eiendomsverdi* obtains information on units advertised for sale on the online platform *Finn.no* that covers more than 70% of the market. The data are combined, and cross-checked, with public registry transaction data. The transaction data used in this article have the same source as the data used in Anundsen and Røed Larsen (2018) and Røed Larsen (2021), but this article's data coverage is wider. The data include, but are not limited to, unit identifier, transaction price, common debt, ask price, date of acceptance of highest bid, listing date (date of online advertisement when unit was put up for sale), unit attributes (e.g., construction type, size, construction year, number of rooms, and lot size), and geographical location. For about half the observations, the data set also includes the appraisal value set by an appraiser.

I trim the data in order to remove extreme observations or observations with missing values, duplicates, suspicious entries, and typos. Common debt[1] is included in sell price, ask price, and appraisal value. I trim on 0.1 and 99.9 percentiles. I study owner-occupier units, and not co-ops,[2] because the co-op ownership type does not have a unique unit identifier for all years in the data set. I use two versions of the data set: (i) transactions with and without appraisal value and (ii) observations with appraisal value.

Table 1 presents summary statistics for the data. The total data set after trimming consists of 691,192 transactions during the period January 1, 2002 and February 1, 2017. Out of these observations, 373,373 have appraisal values. The appraisal data have units with a slightly lower mean size, owing in part to the much higher Oslo share (big cities have a high frequency of small apartments). While the overall data set has a 16% Oslo share, the appraisal data have an Oslo share of 25%. Part of the reason for this is institutional. During the period I study, it was not common in all cities to make use of an appraiser, but it was common in Oslo.[3] For both the overall and the appraisal data, the median sell–ask spread (sell price less ask price on ask price) is zero. For the appraisal data set, the median appraisal spread (sell price less appraisal value on appraisal value) is zero.

The lower panel includes observations from Oslo transactions with appraisal values. We see that these transactions involve smaller units; the median size is 73 m^2 while the overall median size is 111 m^2. While the overall data have an apartment share of 36%, Oslo appraisal data have a share of 80%. Neither the median sell–ask spread nor the appraisal spread for Oslo transactions are zero. This could potentially be due to a rising price trend in Oslo, in which ask prices and appraisal values might have been lagging sell prices. Anundsen et al. (2023) argue that part of this nonzero spread is due to strategies among realtors. Since I use repeat sales, which essentially is taking first differences, it should not affect my results when I compare December coefficients with September coefficients.

[1] Common debt is more common in co-ops, which are not included in the data set. Owner-occupier units sometimes have common debt, but it is rare and then the common debt is small.

[2] Cooperatives are organized such that the occupier buys a right to live within the compound. All occupiers share financial and other responsibilities.

[3] Today, it is no longer common to obtain an appraisal value. The realtor handles the valuation.

TABLE 1 Summary statistics—Transaction data: Norway, 2002–2017.

	Min	25th Percentile	Median	Mean	75th Percentile	Max
Data containing observations with and without appraisal value						
$N = 691{,}192$						
Date	Jan 1, 2002	Oct 19, 2006	Sep 22, 2010	May 4, 2010	Dec 16, 2013	Feb 1, 2017
Sell	326,000	1,600,000	2,275,000	2,640,965	3,225,000	14,750,000
Ask	250,000	1,590,000	2,225,000	2,598,211	3,190,000	18,900,000
Sell–ask spread	−0.305	−0.0303	0.000	0.0185	0.0571	0.573
Size	21	75	111	119	153	378
Sell/size	2874	14,535	21,765	25,297	32,500	100,303
Share Oslo = 0.16						
Share apartments = 0.36						
Data containing observations with appraisal value						
$N = 373{,}373$						
Date	Jan 2, 2002	Jan 31, 2007	Dec 6, 2010	May 29, 2010	Nov 11, 2013	Feb 1, 2017
Sell	330,000	1,680,000	2,375,000	2,772,720	3,392,124	14,750,000
Ask	250,000	1,650,000	2,304,580	2,717,162	3,300,000	18,900,000
Appraisal	250,000	1,690,000	2,350,540	2,768,529	3,370,000	22,000,000
Size	21	72	108	117	150	378
Sell/size	2,874	15,625	23,664	27,082	35,278	100,271
Sell–ask spread	−0.305	−0.0269	0.00253	0.0230	0.0643	0.566
Appraisal spread	−0.375	−0.0476	0.000	0.00556	0.0536	0.543
Share Oslo = 0.25						
Share apartments = 0.40						
Data containing observations with appraisal value: Oslo						
$N = 93{,}716$						
Date	Jan 2, 2002	Aug 23, 2006	Jun 21, 2010	Jan 16, 2010	Aug 9, 2013	Jan 31, 2017
Sell	540,000	2,050,000	2,900,000	3,480,289	4,300,000	14,750,000
Ask	520,000	1,956,875	2,791,499	3,361,810	4,100,000	18,900,000
Appraisal	520,000	2,000,000	2,850,000	3,432,444	4,200,000	22,000,000
Size	21	54	73	89	110	378
Sell/size	5379	30,000	40,411	41,987	52,083	100,271
Sell–ask spread	−0.304	−0.0106	0.0270	0.0430	0.0899	0.555
Appraisal spread	−0.364	−0.0333	0.00885	0.0220	0.0738	0.543
Share apartments = 0.80						

Note: Prices are in NOK. Size in square meters; rounded to square meters. Date is date of acceptance of bid. Prices are in nominal terms and should be interpreted with caution due to the length of the time period.

2.2 | The construction of repeat-sales data

The data include units that are transacted multiple times. These repeat-sales units are, however, not transacted at the same time. In order to construct the repeat-sales data, I follow Case and Shiller (1989) and retain only units that are sold exactly twice. I leave out units that are sold multiple times since they may be different from units sold more infrequently, but I include in the

TABLE 2 Check for balance—Transaction data: Norway, 2002–2017.

	Jan	Feb	Jun	Aug	Sep	Oct	Nov	Dec
No. obs.	47,732	49,134	78,064	64,149	75,853	67,660	56,884	25,245
Size	115.7	116.5	121.1	116.6	121.5	120.1	118.7	116.2
Sell	2,710,504	2,577,618	2,673,142	2,647,516	2,729,536	2,649,470	2,631,532	2,412,158
Ask	2,662,651	2,534,722	2,626,649	2,588,463	2,686,929	2,619,987	2,610,616	2,425,791
TOM	54.8	49.3	33.9	43.9	39.1	39.2	40.5	55.2
Apt. sh.	0.40	0.38	0.33	0.37	0.34	0.35	0.36	0.37
Oslo sh.	0.18	0.17	0.15	0.17	0.16	0.16	0.16	0.14

Note: Sell and ask prices are in NOK. Time-on-market (TOM) is in days; size in square meters. The dates used to compute TOM is the date of acceptance of bid less the date of advertisement posted online (on Finn.no). Prices are in nominal terms and should be interpreted with caution due to the length of the time period.

Appendix a robustness check in which I replicate Table 4 regression on a data set with units that are sold exactly three times. The pattern is intact. In the overall data set, there are 213,394 observations of units sold exactly twice. These observations encompass 111,244 observations of transactions involving units that have transacted exactly twice and, in addition, have appraisal values, that is, there are 55,622 such repeat-sale units in the appraisal data set.

2.3 | The construction of submarket aggregate data

In the analysis of submarkets, I study patterns of geographical variation. To construct the appropriate data set, I first require that municipalities have at least 800 transactions over the period out of a total of 428 municipalities.[4]

I then partition into two types of units: apartments and nonapartments.[5] I left out one submarket with no December sales, and was left with 247 submarkets. In the Appendix, I include results from segmented regressions in which I partitioned on transaction volumes.

2.4 | Institutional background

In Norway, a little less than four out of five households are owner-occupiers. This proportion is slightly different between choices of unit; that is, whether one inspects the status of households, individuals, or housing units. The typical housing career involves renting when studying, then buying the first unit upon entering the first job. As an individual grows older, she typically buys a larger unit and forms a household with a spouse. After retirement, many households sell their house and move into easier-to-maintain and centrally located apartments.

[4] There is an element of art to the choice of a cutoff of 800, and I did experiment with several cutoffs. A higher cutoff leaves us with fewer, but thicker submarkets. A lower cutoff leaves us with more, but thinner submarkets.

[5] Again, there is an element of art into such partitioning. Houses could potentially be further partitioned into detached, semidetached, and row houses. Alternatively, one could partition into segments below and above the median size. These partitions would have left us with more, but thinner submarkets. I chose not to.

TABLE 3 Hedonic model of log sell prices on determinants: Norway, 2002–2017.

	I All data	II Appraisal data
Intercept	12.3*** (176)	11.9*** (118)
Logsize	−0.0980*** (−3.4)	0.0536 (1.3)
Sqlogsize	0.0841*** (29)	0.0711***(17)
Type FE	YES	YES
Interaction	YES	YES
Constr. year	YES	YES
Large lot FE	YES	YES
City FE	YES	YES
Region FE	YES	YES
Weekday*City	YES	YES
Linear trend	0.00470*** (665)	0.00463*** (469)
Jan-June FE	YES	YES
Sep	0.0389***(21)	0.0488*** (19)
Oct	0.0244*** (13)	0.0320*** (12)
Nov	0.0180*** (9.1)	0.0227*** (8.3)
Dec	−0.0117*** (−4.8)	−0.00714* (−2.1)
No. obs.	691,192	373,373
(Deleted due to missingness)	(6,432)	(2,295)
Adj. R^2	0.711	0.721

Note: Interaction variables comprise products of (Oslo,logsize), (Oslo, sqlogsize), (apartment, logsize), and (apartment, Sqlogsize). The specification also includes dummies for construction year periods; see the Data section. City FE refers to the inclusion of dummies for the largest cities in Norway. Region FE denotes dummies for all Norwegian counties, except Oslo, which is also a city, and Troms and Finnmark, which are default. Weekday*City involves five dummies for each of the days in the work-week, Monday–Friday, multiplied by dummies for Oslo and Bergen. Linear trend denotes a counting variable that counts month number since January 2002, which is default. I use the vcovHC function to obtain robust standard errors. I compute a t-statistic (presented in parentheses) and set the threshold levels for 0.05 (*), 0.01 (**), and 0.001 (***) levels of statistical significance to 1.96, 2.58, and 3.30, respectively, since we have many degrees of freedom.

Geographically, Norway is a relatively large country with few inhabitants. There is a substantial difference between rural areas and urban centers, and there is considerable heterogeneity at the local submarket level (Røed Larsen, 2021). This geographical variation allows us to study the comovement of prices and market activity and test the hypothesis that the December discount is more pronounced in submarkets with more pronounced transaction seasonality.

2.4.1 | Auctions

The Norwegian housing market is organized around a transaction process that involves an ascending-bid (English) auction. This auction commences the day after the last open house (public showing). Since house sales are arranged in this manner, this auction process must not be confused with forced sales, of which there are very few in Norway. The realtor leads the auction and informs participants, both active bidders and interested parties, about the bidding activity.

TABLE 4 Repeat sales of log(sell price): Norway, 2002–2017.

	Data with and without appraisal value			Data with appraisal value		
	I	II	III	IV	V	VI
	OLS	Unit FE	Unit FE	OLS	Unit FE	Unit FE
Year FE	YES	YES	YES	YES	YES	YES
Jan-Aug FE	YES	YES	YES	YES	YES	YES
Unit FE	NO	YES	YES	NO	YES	YES
log(ask)			0.868*** (544)			
log(app)						0.783*** (288)
September	0.130*** (26)	0.0144*** (9.4)	0.00806*** (10)	0.151*** (21)	0.0134*** (6.6)	0.00794*** (6.4)
October	0.118*** (23)	0.0144*** (9.1)	0.00495*** (6.1)	0.131*** (18)	0.0126*** (6.1)	0.00506*** (4.0)
November	0.106*** (20)	0.0113*** (6.9)	0.000302 (0.36)	0.116*** (15)	0.00619** (2.9)	−0.00223 (−1.7)
December	0.0457*** (7.0)	0.0113*** (5.6)	−0.00482*** (−4.7)	0.0598*** (6.5)	0.00697** (2.7)	−0.00689*** (−4.3)
	No. sales = 2			No. sales = 2		
	N = 213,394			N = 111,244		
Adj. R^2	0.212	0.590	0.885	0.180	0.636	0.857

Note: Repeat-sales data include units that are transacted exactly two times in the 2002–2017 period. Log(ask) and log(app) are short notation for the logarithms of ask price and appraisal value. FE is short notation for a fixed effect regression run using the plm-function in R and the within-model. Year FE denotes a collection of year dummies (2002 default). Jan-Aug FE denotes a collection of 7-month dummies from January to August, excluding July (default). I use the R-function lm to estimate models I and IV and the plm-function to estimate models II, III, V, and VI. I use the sandwich and vcovHC functions to obtain robust standard errors, clustered on zipcode, after having demeaned the data. I compute a t-statistic (presented in parentheses) and set the threshold levels for 0.05 (*), 0.01 (**), and 0.001 (***) levels of statistical significance to 1.96, 2.58, and 3.30, respectively, since we have many degrees of freedom.

In recent years, bids are extended digitally, which involves a countrywide digital identification system.[6] All bids are legally binding, but conditional bidding is allowed.[7]

Acceptances of bids are legally binding. The implication is that once the highest bid is accepted transfer of ownership between seller and buyer is locked in. In contrast to the situation in other Nordic countries, there is no grace period in which market participants may walk away from the agreement. This means that, in principle, it is possible in Norway to construct a daily price ticker of house prices (see Anundsen et al., 2023 for an application).

2.4.2 | The ask price and the appraisal value

Until 2016, it was common practice in most cities that the realtor contacted an appraiser who would inspect the unit, issue a technical report, and announce an appraisal value. After 2016, the appraisers typically concentrate their effort on the inspection report and do not announce an appraisal value. Part of the reason for this change is that the typical background of the appraiser is in engineering and it was considered more appropriate to let realtors handle the market side. The appraisal value that was commonly issued before 2016 was an independent value assessment, neither related to taxation nor the financial situation of the buyers. A buyer's ability to obtain a loan is connected to his or her household's income and home equity.[8] While the mortgage in today's regulatory framework cannot exceed 0.85 of the final price of the unit to which the mortgage is tied, rules were different throughout the period I study. The appraisal value was issued before the auction and did not in itself impose any constraints on the bidding.

Before the online advertisement, the realtor and the seller discuss what ask price to announce. The seller has some room for maneuver in setting the ask price, but there is regulation requiring that the realtor must ensure that the ask price is realistic and reflects the seller's reservation price to a high degree. [9]

Sellers put their unit up for sale on the online platform Finn.no. In the advertisement, they announce both the ask price and one or several dates for the open house (public showings) on which any interested buyer may come and inspect the unit. Typically, a seller in Oslo lists the advertisement on a Friday and announces the open house for the Sunday or Monday 9 and 10 days, respectively, later. The advertisement includes all relevant information about the unit and typically has a large number of photographs. This information makes it possible for prospective buyers to obtain a sense of the match between their preferences and the attributes of the unit, and thus to make informed decisions on which open houses to visit. Due to the time it takes to visit an open house, no buyer can visit more than a small fraction of the open houses on any given Sunday.

[6] Earlier, fax machines could be used.

[7] Conditions may include contingencies upon financing or takeover dates. Often, conditions include expiration times, for example, a statement that the bid is valid for 3 hours.

[8] For more information on Norwegian appraisers, see norsktakst.no.

[9] If the authorities discover that a realtor agency systematically is associated with multiple transactions in which the ask price is set artificially low, for example, if there is a high frequency of rejected bids above the ask price, sanctions may be issued.

3 | IDENTIFICATION AND EMPIRICAL METHODOLOGY

3.1 | Identification strategy

In a fully specified hedonic model that accounts for trend and cycle, an estimator of the December effect is the coefficient of a dummy variable for sell date in December. However, if there is unobserved heterogeneity this estimator could be biased. The unobserved heterogeneity could be time-invariant (e.g., view, layout) or time-varying (e.g., renovation, neighborhood). In this section, I explain this article's identification strategy, which includes handling unobserved heterogeneity.

Let a unit i be sold two times. For the first transaction, the sell price P, the ask price A, and the appraisal value APP are determined on dates t, r, and r, respectively. Since TOM in Norway is short, $t - r$ is most often less than 100 days, often much shorter (see Table 2). In fact, in Oslo TOM is often less than 30 days. In practice, the dates of the ask price and the appraisal value are close to each other, thus we set both to r, and we refer to r as the listing date. We can write:

$$\begin{aligned} P_t &= T_t + X + Y + Z_t + \delta D_t + u_t, \\ A_r &= T_r + X + Y + Z_r + g_r, \\ APP_r &= T_r + X + Y + Z_r, \end{aligned} \tag{1}$$

in which T captures the general house price level at time t, X represents the observable hedonic attributes, Y represents unobserved time-invariant component, Z is the unobserved time-varying component, u is stochastic noise, g is a potential premium markup in the ask price. The unit subscript i and the coefficients for X, Y, and Z are suppressed to ease reading. I have, however, included the coefficient δ in order to highlight our interest in this coefficient since it is the estimator of the December effect. X and Y are time-invariant, thus I do not subscript with time. The ask price and the appraisal value do not contain the component δD_t since neither the seller nor the appraiser would know the sell date at the time when the ask price and the appraisal value are set.

For the second transaction of the same unit i, the sell price P, the ask price A, and the appraisal value APP are determined on the dates s and q. We refer to s as the sell date and q as the listing date. As an illustration on how to use repeat sales to identify the December discount, let the date t be in December and s not in December.

$$\begin{aligned} P_s &= T_s + X + Y + Z_s + u_s, \\ A_q &= T_q + X + Y + Z_q + g_q, \\ APP_q &= T_q + X + Y + Z_q. \end{aligned} \tag{2}$$

The identifying strategy of the December discount starts by first finding the difference between the sell price P and the ask price A for the first and the second transactions. In econometric practice, this would be done by including the ask price as a control in a hedonic regression of sell price (or, alternatively, compute the sell–ask spread, i.e., the difference between the sell price and the ask price as a fraction of the ask price). Keeping in mind that $D_t = 1$ and $D_s = 0$, we obtain:

$$(P_t - A_r) = T_t + X + Y + Z_t + \delta + u_t - T_r - X - Y - Z_r - g_r,$$

$$= T_t - T_r + Z_t - Z_r + \delta + u_t - g_r,$$

$$(P_s - A_q) = T_s + X + Y + Z_s + u_s - T_q - X - Y - Z_q - g_q, \quad (3)$$

$$= T_s - T_q + Z_s - Z_q + u_s - g_q,$$

since the components with hedonic attributes X and the time-invariant component Y vanish in first differences. If:

$$Z_t - Z_s = Z_r - Z_q,$$

$$T_t - T_s = T_r - T_q, \quad (4)$$

then

$$(P_t - A_r) - (P_s - A_q) = T_t - T_r + Z_t - Z_r + \delta + u_t - g_r$$

$$-T_s + T_q - Z_s + Z_q - u_s + g_q, \quad (5)$$

$$= \delta - g_r + g_q + u_t - u_s,$$

and then we have identified the December effect δ as long as there are no seasonality effects in setting the ask price, that is, $g_r = g_q = 0$. Thus, our identification strategy consists of three conditions:

1. Substantiate that $g_r - g_q = 0$ or approximately so;
2. Substantiate that $Z_t - Z_s = Z_r - Z_q$ or approximately so;
3. Substantiate that $T_t - T_s = T_r - T_q$ or approximately so.

Ultimately, 1–3 are empirical questions, and below I shall argue that they hold to a reasonable extent.

3.2 | The three identification conditions

The substantiation that the first condition is satisfied is straightforward since it amounts to showing that there is no seasonality in ask prices. To that end, I use appraisal values and examine the difference between ask price and appraisal value:

$$A_r - App_r = T_r + X + Y + Z_r + g_r - T_r - X - Y - Z_r$$

$$= g_r. \quad (6)$$

Thus, substantiating element 3 in the identification strategy entails testing for seasonality in the ask price while controlling for appraisal. I do this in two ways: (i) regress the ask–appraisal

TABLE 5 Segmentation on time-on-market (TOM)—Appraisal data, repeat sales: Norway, 2002–2017.

	Appraisal data log(sell)	
	FE	FE
TOM segment	0–21 days, both sales	22- days, both sales
	a	b
log(app)	0.808*** (226)	0.838*** (156)
Year FE	YES	YES
Jan-Aug FE	YES	YES
Unit FE	YES	YES
September	−0.00200 (−1.2)	−0.0101*** (−5.0)
October	−0.00254 (−1.4)	−0.0129*** (−6.3)
November	−0.00822*** (−4.6)	−0.0170*** (−8.0)
December	−0.00862*** (−3.8)	−0.0117*** (−4.7)
	No. sales = 2	
No. obs.	61,466	25,356
Adj. R^2	0.890	0.864

Note: In column a, I first segment appraisal data on TOM equal to or below 21 days, then retain only units that are sold exactly twice. Notice that multiple observations are lost because one TOM is above 21 days. Log(app) is short notation for the logarithm of the appraisal value. In column b, I first segment appraisal data on TOM equal to or larger 22 days, then retain only units that are sold exactly twice. FE is short notation for a fixed effect regression run using the plm-function in R and the within-model. Year FE denotes a collection of year dummies (2002 default). Jan-Aug FE denotes a collection of 7-month dummies from January to August, excluding July (default). I use the sandwich and vcovHC functions to obtain robust standard errors, clustered on zipcode. I compute a t-statistic (presented in parentheses) and set the threshold levels for 0.05 (*), 0.01 (**), and 0.001 (***) levels of statistical significance to 1.96, 2.58, and 3.30, respectively, since we have many degrees of freedom.

spread[10] on to a space spanned by year fixed effects and calendar months, (ii) regress the log(ask price) onto a space spanned by log(appraisal value), year FE, and calendar months. In the regressions, I use listing dates to obtain year and calendar month dummies, not sell dates. The results are tabulated in Table A.1. The first regression of the ask–appraisal spread yields only two statistically significant coefficient estimates of the calendar month dummies, September and October. The second regression yields statistically significant coefficient estimates for the first 3 months of the year, January–March (requiring t-values above 2.6), but not for other months. The results are consistent with a notion that ask prices might have a slight seasonal component. Overall, however, the results indicate that the first identification condition holds when the aim is to estimate the December effect on sell prices.

Conditions 2 and 3 involve another approach. For the second condition, we do not observe the latent variable Z, which captures unobserved time-varying heterogeneity. However, since we seek to investigate whether the difference in Zs between the two sell dates is equal to the difference in Zs between the two listing dates, it should suffice to show that the number of days between the two sell dates, $s - t$, is equal to the number of days between the two listing days, $q - r$. In Table A.2, I present a regression of $s - t$ onto $q - r$ for 213,394 transactions. The estimated coefficient is 0.995 and the adjusted R^2 is 0.993, suggesting that the time span between the two sale dates and the two

[10] The ask–appraisal spread is the difference between the ask price and the appraisal value as fraction of the appraisal value.

TABLE 6 Repeatability of time-on-market (TOM) for each unit: Norway, 2002–2017.

	Data with and without appraisal values		
	I	II	III
	OLS	OLS	FE
		Dependent variable	
	TOM second sale	TOM	TOM
Intercept	36.4*** (143)	52.7*** (55)	
TOM first sale	0.0838*** (20)		
Year FE	NO	YES	YES
Jan-Au FE	NO	YES	YES
Unit FE	YES	NO	YES
September		−9.59*** (−11)	−6.53*** (−8.3)
October		−10.5*** (−12)	−6.45*** (−8.2)
November		−9.22*** (−11)	−5.57*** (−6.9)
December		5.19*** (4.5)	5.32*** (5.2)
		No. sales = 2	
No. units	106,697	106,697	106,697
R^2	0.00653	0.0164	0.0184
Adj. R^2	0.00652	0.0162	−0.964

Note: The regression was run on a data set in which units have been observed sold exactly twice. TOM is computed as the difference in days between the date on which the unit was announced for sale on the online platform Finn.no and the date on which the highest bid was accepted. I use the sandwich and vcovHC functions to obtain robust standard errors, clustered on zipcode. I compute a t-statistic (presented in parentheses) and set the threshold levels for 0.05 (*), 0.01 (**), and 0.001 (***) levels of statistical significance to 1.96, 2.58, and 3.30, respectively, since we have many degrees of freedom.

listing dates are highly similar. This allows us to claim that the second condition of identification should be met.

For the third condition, we could estimate the index levels at the four dates t, s, r, and q. Again, since we are interested in the equality of two differences of the general price level T, it should suffice to show that $s - t$ is approximately equal to $q - r$. The regression results in Table A.2 show that the number of days between the two sell dates is more or less equal to the number of days between the two listing days, thus the price level differences in the same sale pair would be equal and so the third condition should be met.

3.3 | The hedonic model

I start my empirical estimation by estimating a hedonic model. The model is similar in spirit to, and is based on the same data source (although wider in coverage), as in Anundsen and Røed Larsen (2018) and Røed Larsen (2021). The baseline model is a hedonic model of the logarithm of sell price (including common debt) onto a space spanned by determinants:

$$\log(P_i) = \alpha + \beta_1 \log(Size_i) + \beta_2(\log(Size_i))^2 + \sum_K \gamma_k X_{i,k} + \eta m_i + \sum_{c=1}^{11} \theta_c M_{c,i} + \varepsilon_i, \quad (7)$$

TABLE 7 Regressions of market observations—Market sell–ask spread differential on market activity in December: Norway, 2002–2016.

	Transaction data			
	Sell–ask spread differential. Dec less not December			
	All markets		Long TOM	Short TOM
Market activity measure:	sales	ads	sales	sales
	a	b	c	d
Intercept	−0.0336*** (−6.5)	−0.0250*** (−10)	−0.0382*** (−4.0)	−0.0332*** (−6.0)
Rel. Dec. vol.	0.0285** (2.6)		0.0315 (1.6)	0.0348** (2.7)
Rel. Dec. for-sale		0.00200* (2.5)		
No. of markets	247	247	124	123
Adj. R^2	0.0462	0.0381	0.0405	0.0852

Note: The regressions were run after partitioning Norway into different markets. First, I removed municipalities with less than 800 transactions in the period. This leaves us with 627,405 transactions. Then, I partitioned each municipality into apartments and nonapartments (detached houses, semidetached houses, and row houses). I also removed transactions from the year 2017 since my records are not complete for this year. Markets with no December transactions were removed. For each market, I compute the mean sell–ask spread in December and non-December and the transaction volume in December and non-December. I also compute number of units that were put up for sale in each market (listings) for December and non-December. The for-sale registration date is the date on which the unit was announced for sale on the online platform Finn.no. The variables Relative December transaction volume and Relative December for-sale registration are the number of transactions and registrations in December as fractions of the mean of the other 11 months. Thus, the regressions are the difference between the December spread and non-December spread on the ratio of December activity and non-December activity. Long time-on-market (TOM) and short TOM markets were defined as markets with intramarket mean TOM above or equal to across-markets median TOM and intramarket mean TOM below across-markets median TOM, for example, a market belongs to the short TOM segment if the mean TOM in that market is below the median TOM among the within-market means across markets. The standard errors were computed using the vovHAC-function. I compute a t-statistic (presented in parentheses) and set the threshold levels for 0.05 (*), 0.01 (**), and 0.001 (***) levels of statistical significance to 1.96, 2.58, and 3.30, respectively, since we have many degrees of freedom.

in which the subscript i refers to unit i, $X_{i,k}$ denotes attribute k in a collection of K attributes that characterize unit i. The term m_i is a counting variable that takes on the running number (across the period) of the month in which the transaction of unit i took place.[11] For example, if unit i was sold in the 23rd month in the period, $m_i = 23$. $M_{c,i}$ is a collection of 11 calendar month dummies. A dummy takes on the value 1 if the transaction of unit i took place in that calendar month and 0 if it did not. For example, if unit i was sold in March, $M_{3,i} = 1$. Notice that I do not subscript the time when a unit is transacted; instead the terms m_i and $M_{c,i}$ incorporate the temporal element of the general price level, presented as the general term T above. The term ϵ_h is a stochastic element. The collection of attributes includes dummies of type, interaction variables of type and the size polynomial, interaction variables of Oslo and the size polynomial, a collection of construction periods which is unity if the unit was constructed in that period,[12] city dummies for the largest cities in Norway, regional dummies for the administrative regions (counties) Norway consisted of

[11] The month number (counting variable) runs from the first to the last month in the sample period, January 2002–February 2017

[12] The collection of construction year dummies consists of three periods, 1950–1979, 1980–1999, and after 2000. The period before 1950 is default.

during the period,[13] and a weekday-city interaction variable for the two largest cities, Oslo and Bergen.[14]

Notice that I use the subscript i as short notation for the transaction of house i. If the house is sold two times, a more precise notation would be i_1 and i_2, and these transaction observations will occur in the data set as separate observations. However, in the model statement above both transactions are referred to as i even though the entries into the terms m_i and $M_{D,i}$ will be different on the two times unit i was sold. Transaction of unit i is defined as having taken place on the date on which the highest bid was accepted since acceptance of bids (as well as bids themselves) are legally binding in Norway. Sell price, ask price, and appraisal value include common debt.

3.4 | The repeat-sales setup

In order to handle the time-invariant unobserved heterogeneity represented above by Y, I use a repeat-sales approach in which the hedonic attributes X are identical for repeat sales of unit i and are represented by the individual term α_i. The general price level T is handled by year and calendar month fixed effects:

$$\log(P_{i,n}) = \alpha_i + \sum_{yr=2003}^{2017} \theta_{yr} E_{yr,i,n} + \sum_{c=1}^{11} \theta_c M_{c,i,n} + \varepsilon_{i,n}, \tag{8}$$

in which E_{yr} denotes a collection of 15 year dummies and n refers to the sales number of unit i. The subscript yr refers to year and c to calendar month. I use a data set in which I retain units that were sold exactly twice (following Case & Shiller, 1989), but as a robustness check I also estimate the coefficients for a data set in which I retain units that were sold exactly three times. Thus, a unit i appears in the data set two times, $n = 1$ and $n = 2$, and a unit ID ensures the unit fixed effect setup. In order to handle time-varying unobserved heterogeneity represented above by Z, I use the repeat-sales approach by augmenting the list of determinants with log(ask) or log(appraisal).

3.5 | Price seasonality across subsegments

For each of 247 submarkets, I construct a measure of price seasonality as manifested in a December effect. I compute the mean sell–ask spread (defined as the difference between the sell price and the ask price as a fraction of the ask price) in December and the mean sell–ask spread in the other 11 months (excluding the year 2017 for which we only have observations in January and February). I use the spread, not the sell price, since the ask price both reflects a time trend and accounts for attributes and quality of the unit. Moreover, I use the spread and not a log(sell) less log(ask) difference because it is easier to interpret. The spread captures the extent to which the sell price exceeds an expected value. My price seasonality measure is the difference between the two spreads, that is, the difference between the December spread and the non-December spread. Thus, even though I use spreads, the ask prices are only tools for controlling for unobserved quality. The

[13] The exceptions are Oslo, which is also a city (the capital), and Troms and Finnmark, which together constitute the default region.

[14] Røed Larsen (2021) demonstrates that there are intraweek price patterns in the Norwegian housing market driven by the mode of the distribution of the day of the open house.

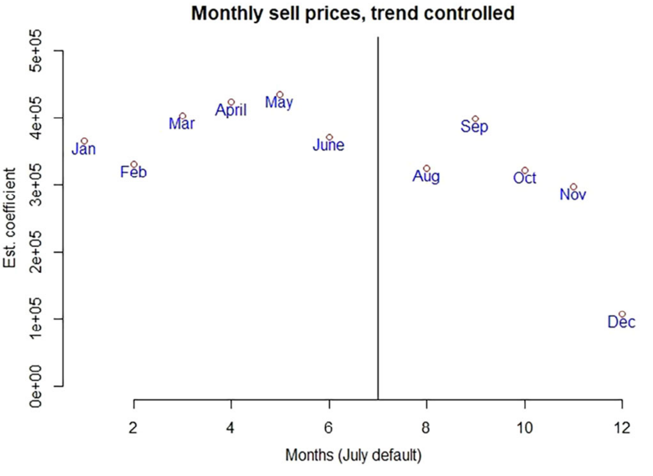

FIGURE 1 House price seasonality. Norway, 2002-2017
(*Notes*: Coefficients are estimated using a regression model in which sell prices are regressed onto a month counter running over months within 2002-2017 and calendar month dummies (July is default). I plot estimated coefficients for month dummies. The data cover the period described in the upper panel of Table 1.)
[Color figure can be viewed at wileyonlinelibrary.com]

implication is that seasonality in spreads amounts to seasonality in prices, given that the three identification conditions are met.

I use two measures of market activity, one based on transactions and one based on listings (advertisements). The transaction-based measure is the ratio of the mean number of transactions in a given submarket in December relative to the mean number of transactions in the same submarket in the other 11 months. The listings-based measure is the ratio of the mean number of new listings in a given submarket in December relative to the mean number of new listings in the same submarket in the other 11 months.

4 | EMPIRICAL RESULTS

4.1 | The regularity of a December price drop

Figure 1 displays the estimated coefficients of month dummies in a regression of sell price onto a space spanned by a linear counter in month number since January 2002, to capture a time trend, and additive calendar month dummies. This figure is meant as a motivating example of the December price drop, and I make no attempts here at controlling for any attributes. The idea is that the figure illustrates what realtors and market participants have noted. We do observe that the estimated coefficient for December is substantially lower than other months, which reflects the lower trend-controlled sell prices in December.

4.2 | Composition effects

I examine the possibility that units sold in December are different from units sold earlier in the Fall. I first perform a check for balance of key attributes of the unit (size, type, and location) and key attributes of the transaction (sell price, TOM). Table 2 tabulates the results of the check for balance. We observe that transacted units tend to be somewhat smaller in December (116 m^2) than in September (122 m^2) and that apartments tend to have a larger share in December (37%) compared to September (34%). We also observe that the sell price is 10% lower (NOK 2.4 mill) in

December compared to September (NOK 2.7 mill), but we realize that much of this substantial price difference can be ascribed to the composition effect. However, prices are in nominal terms and should be interpreted with caution due to the length of the time period.[15] TOM is 55 days in December, which is considerably longer than the 39 days in September. The transaction volume in December is one third of the volume in September, 25,245 sales versus 75,853 sales. Table 2 indicates that both the composition of transacted units and the market conditions are different in December.

4.3 | Controlling for composition bias, attributes, and time trend

In order to disentangle the December effect from a composition bias, I start out by controlling for observed attributes through the estimation of a hedonic model. I employ the baseline hedonic model, and it is estimated on two data sets: the data set that contains both observations with and without appraisal and the subset that contains observations with appraisal values. The estimated dummy coefficients for December are −0.0117 and −0.00714, while the coefficients for September are 0.0389 and 0.0488. Having controlled for composition, attributes, and a time trend, the results show a clear December discount. These estimates indicate a December discount of 5%.

4.4 | Unobserved heterogeneity

Having controlled for composition, attributes, and time trend, we are left with the challenge of unobserved heterogeneity. If negative unobserved qualities are associated with units transacted in December, the December dummy estimate would contain both a season effect and a quality effect.

I deal with unobserved heterogeneity in units by combining two remedies, a repeat-sales model in which the same unit is sold twice and a setup that uses information on the ask price and appraisal value. As a preliminary exercise, Figure 2 plots the seasonality in sell–ask spread, sell–appraisal spread, and the ask–appraisal spread. The first two spreads include the sell price, which has a large seasonality component. The last spread is based on ask price and appraisal value in which we observe almost no seasonality.

We see from the left and middle graphs of Figure 2 that when we control for unobserved time-invariant attributes, which are reflected in the ask price and appraisal value, in addition to a linear trend, the December discount pattern remains in the sell price. The December spreads are lower than spreads in September, October, and November.

Table 4 tabulates the results from regressions of log(sell price) using repeat-sales data. Models I and IV are ordinary least-square models and they are included for comparison. Models II, III, V, and VI are unit fixed effect models. Models III and VI include controls for time-varying unobserved heterogeneity, and may thus be considered the full models. For both types of data, we see that for models III and VI the estimated December coefficients are substantially lower than the coefficients for September–November. The December discount pattern is intact when we control for unobserved unit heterogeneity.

I view Table 4 as my main exhibit. The repeat-sales structure controls for time-invariant unobserved unit heterogeneity and the employment of ask price and appraisal value controls for time-varying unobserved unit heterogeneity. In addition, the use of appraisal value takes care of possible seasonality or strategy in ask prices. We observe that the December coefficient is smaller

[15] I control for a time trend in analyses below.

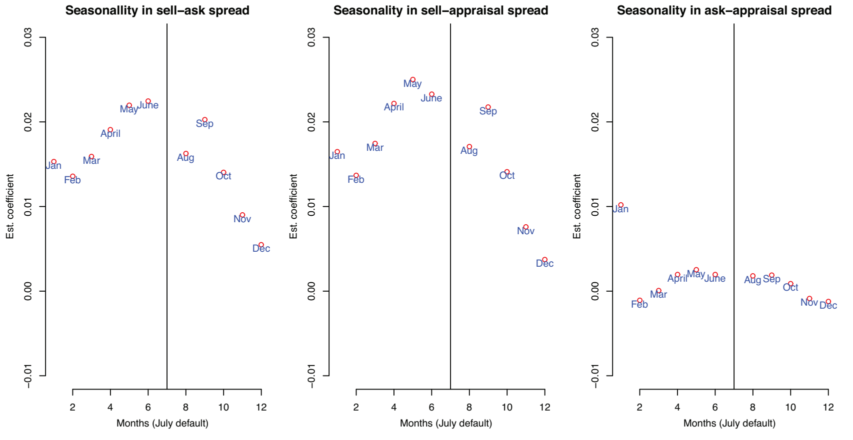

FIGURE 2 Seasonality in sell-ask, sell-appraisal, and ask-appraisal spreads. Norway, 2002-2017 (*Notes*: The coefficients are estimated using a regression model in which sell-ask, sell-appraisal, and ask-appraisal spreads are regressed onto a space spanned by year dummies for 2003-2017 (2002 default) and calendar month dummies (July default). The dummies are constructed using sell dates for all spreads. I plot estimated coefficients for month dummies. The graph in the left-hand panel was generated using all transaction data, described in the upper panel of Table 1. The two other graphs were generated using appraisal data, described in the middle of Table 1.
[Color figure can be viewed at wileyonlinelibrary.com]

than the coefficients of September, both when we use the larger data set that relies on ask prices and when we use the smaller data set that uses appraisal values.

When the larger data set is used and ask price is used as a control, that is, model III, the difference between the September (0.00806) and the December (−0.00482) coefficients is 0.013. This implies a discount estimate of 1.3%. When we use data with appraisal value and use appraisal value as control, that is, model VI, we obtain an estimated discount of 1.5%. Table A.3 estimates model III on data in which each unit has been transacted exactly three times. Then, December prices are 1.5% lower than they are in September.

The estimated December discount ranges from 1.3% to 1.5%. This estimate is considerably smaller than the range using models I and IV, which are OLS regressions with monthly dummies, of 8.4% and 9.1%. Models I and IV are parsimonious models that do not account for composition effects. Table 3 reports results from augmented hedonic regressions in which there are attributes, location variables, and interaction effects. Then, the December discount is estimated at 5.1% and 5.6%. When the repeat-sales setup is used, but when the information contained in ask prices and appraisal values are not used, that is, models II and V, the December discount is estimated at 0.3% and 0.6%. Thus, it appears that utilizing the information contained in ask prices and appraisal values is valuable.

5 | EXPLORATION OF MECHANISMS

5.1 | Duration of sale

In the exploration of the determinants of price seasonality, the natural starting point is market activity. The idea is that the arrival of bidders is a stochastic variable, outside of the control of the seller. When there is seasonality in market activity, the likelihood is high that it implies seasonality

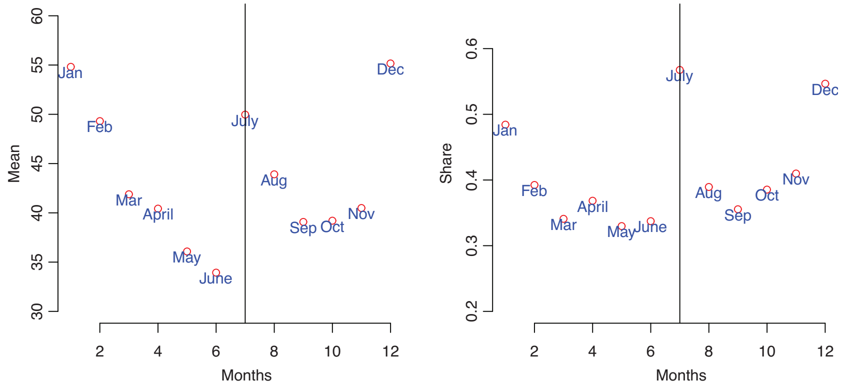

FIGURE 3 Mean TOM and share long TOM (> 21 days). Norway, 2002-2017
(*Notes*: The graphs were generated using all transaction data, described in the upper panel of Table 1.)
[Color figure can be viewed at wileyonlinelibrary.com]

in sell prices because of the mechanism that fewer high-quality matches lead to high prices. One implication of a random arrival of bidders is that units are randomly sorted into short and long TOM. Some units that are put on the market in August and September are sold rapidly due to a random process while other units end up as unsold in December. These units receive fewer bidders and bids and, if sold, have a higher likelihood of obtaining lower prices. This is a testable implication using segmentation based on TOM. The idea is that if it is the long TOM that explains the reduction in sell prices in December, then there should be no differences in sell prices between similar units with a TOM of *t* days in September and *t* days in December.

I reestimate the regressions from above while controlling for TOM. In order to handle the approach to the outcome variable TOM, I first segment into two segments based on TOM, then run the regression without TOM. The results are tabulated in columns a and b in Table 5. We observe that for the long TOM segment, (i) there is little difference between the estimated coefficients of September, October, November, and December, indicating that when we look at only sales of units that had a long duration on the market (as inventory), the differences are minimal and (ii) the estimated coefficients are clearly negative, indicating that these units sell at low prices given their attributes captured by log(appraisal). The interpretation is that if a unit in September had been sold with a TOM typical of December, then the resulting sell price, given attributes, would tend to be as low as it typically is in December.

For the short TOM segment, (i) there is a small difference between the estimated September coefficient and the estimated December coefficient and (ii) the coefficients are closer to zero. The interpretation is that there still is a slight December discount effect, of magnitude 0.7%, but that the short-TOM units tend to sell closer to expected levels given log(appraisal).

In this two-sale data set, there were 1,658 sales with TOM shorter than 21 days in December compared to 6,794 in September. In December, there were 1,310 sales with TOM 22 days or longer compared to 2,496 in September. Put differently, there were 4.1 times more sales with short TOM in September compared to December while there were 1.9 times more sales with long TOM in September compared to December. Thus, TOM tends to be longer in December and appears to play a role in the December discount.

Figure 3 illustrates the seasonality in TOM. It plots mean TOM across months and shows that there are noticeable differences in TOM across months. In the spring and the early summer months of May and June, TOM is at its lowest. These months also have the lowest share of long TOM transactions, as defined by the share of TOMs above 21 days. We notice that mean TOM is almost as long in July as it is in December, and we observe that the share of long TOM transactions is at least as large in July as in December. The origin of the long TOM in July is most likely different from the origin of the long TOM in December since July is a month in which the frequency of travelling abroad is high. The common denominator is low market activity. To support the claim that the July TOM might be related to travelling, I include in Figure 5 the number of passengers on international flights at Norwegian airports for 2015. In July, there were 2,422,082 registered passengers while there were 2,037,578 and 2,017,636 for June and August, respectively. For the months November, December, and January, the numbers were 1,367,588; 1,289,958, and 1,192,149, respectively. These passenger numbers support the notion that July is more different from June and August than December is compared to November and January.

5.2 | TOM for a given house in the first and second transactions

Since TOM in an individual transaction appears to be related to the eventual sell price of a given unit, it is possible that TOM is an outcome variable that is associated with unobserved unit heterogeneity. If so, some units should tend to have long TOMs; other short TOMs given that the relevant qualities are constant across sales. The implication of this possibility is that a unit's TOM should be forecastable on the basis of that unit's TOM in an earlier transaction. In Table 6, I present evidence to the contrary. The table tabulates results from a regression in which the second TOM for each unit is regressed onto the first TOM. We make two observations. First, the adjusted R^2 is 0.00651. Thus, only a little more than half of 1% of the variation in the second TOM is explained by the variation in the first TOM. Second, for each additional first-sale TOM of 10 days, the second-sale TOM increases by less than 1 day. Thus, there is substantial reversion to the mean and little persistence. This evidence suggests that TOM in Norway is not linked to the units themselves; rather, TOM is determined by other processes. Put differently, it is not the case that some units tend to have long TOMs and other units short TOMs.

In columns II and III, I estimate repeat-TOM models based on data with units that have been sold exactly two times. Model II is a simple OLS model of TOM regressed onto a space spanned by year and calendar month dummies. Model III is a unit fixed effect model with year and calendar month dummies. We observe that for model III, the estimated September and December coefficients are −6.5 and 5.3, respectively. Thus, when the same unit is once sold in September and once in December, the estimated difference in TOM would be 12 days longer for the December sale.

5.3 | Market activity

In Table 7, I present results from a regression of market spreads[16] on market activity. First, I identify municipalities with a sufficient amount of transactions, then I compute the sell–ask spread for December and January–November for each submarket and take the difference. I regress the mean submarket sell–ask spread differences onto relative December versus non-December market activities. Here, market activity is measured in two ways, transaction volume (models a, c, and

[16] Again, the sell–ask spread is the difference between sell price and ask price as fraction of ask price.

d) and number of new advertisements of for-sale units (listings) (model b).[17] The market activity measures are constructed as ratios, December volume on non-December volume and December listings on non-December listings.

We observe that in all four regressions the sign is positive, thus there is an association between market activity and the sell–ask spread. Using the sell–ask spread is convenient because the ask price reflects unobserved unit heterogeneity and it also encompasses the price trend. Models a, c, and d use transaction volumes as a metric of market activity. Since there could be an endogeneity issue in that both the spread and the transaction volume are based on the acceptance of the highest bid, I also include model b, which uses the number of new advertisements of for-sale units (listings) as a metric of market activity.

Results from regressions a, b, and d vary in statistical significance, but the pattern of an association between market activity and the sell–ask spread is clear. Regressions c and d are run on segments of markets. We observe that the effect is clearest in the short TOM segment. In sum, the evidence appears to indicate an association between market activity and sell–ask spread. More activity is associated with larger spread, and so these findings are consistent with the notion that the December discount is associated with low market activity in December. The pattern is robust against partitioning into segments based on sales volume, as can be seen in Table A.4, which reports results from similar regressions on segments of transaction volume. Again, higher relative December sales volume is associated with higher relative December spread.

6 | DISCUSSION

To explore market activity in more detail, one avenue is to study the arrival of new listings. After all, the frequency with which new sellers arrive in the market contributes to the determination of the activity in the market since most sellers also participate on the buy side. In Figure 4, the left-hand side panel plots the number of new listings[18] for each month in Norway during the period 2002–2016. The month with the highest number of new listings is May. The month that has the lowest number of new listings is December. This low rate of arrival of new inventory translates into fewer matching opportunities, which in turn imply lower rate of bids, as long as inventory from earlier months does not offset the effect. We observe that July also is a month with a low number of new listings, but the mechanisms behind July-listings is likely to be different from the mechanisms behind the December-listings since we observe a sharper difference between July and its two neighboring months than between December and its two neighboring months. The most likely explanation for the low frequency of listings in July is vacationing, thus traveling might be related to this pattern. This hypothesis is consistent with the patterns of number of passengers seen in Figure 5.

If buyers observe that fewer units are put on the market, their estimates of the probabilities of good matches change. The implication is that the new inventory is associated with longer TOM since the new units stay unsold longer. The right-hand side panel of Figure 4 plots the number of units that have not been sold within a given day, up to 30 days, that is, the survival rate, for each

[17] Note that these for-sale advertisements represent units that were eventually sold since my data set is a transaction data set. At the time, there were, presumably, some advertisements for units that were never sold and thus were never included in the transaction data set. I do not have information on the never-sold units.

[18] As measured by transaction data. Some new listings are never sold and thus are not observed in the transaction data set.

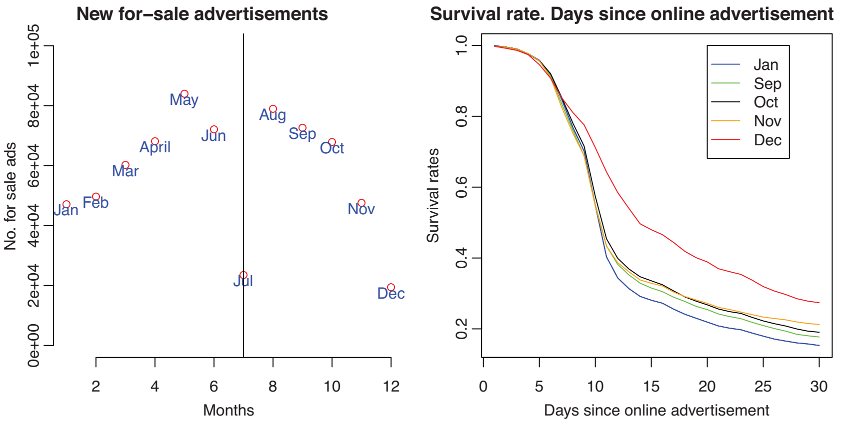

FIGURE 4 New listings (Norway) and survival rates (Oslo), 2002-2017
(*Notes*: The left-hand side panel plots the mean number of new for-sale units listed on the online platform for each month in Norway. The right-hand side panel graphs segments of months of online registration and plots the rate of unsold units (survival rate) in Oslo for each day 1-30 since the listing was posted on the online platform Finn.no.)
[Color figure can be viewed at wileyonlinelibrary.com]

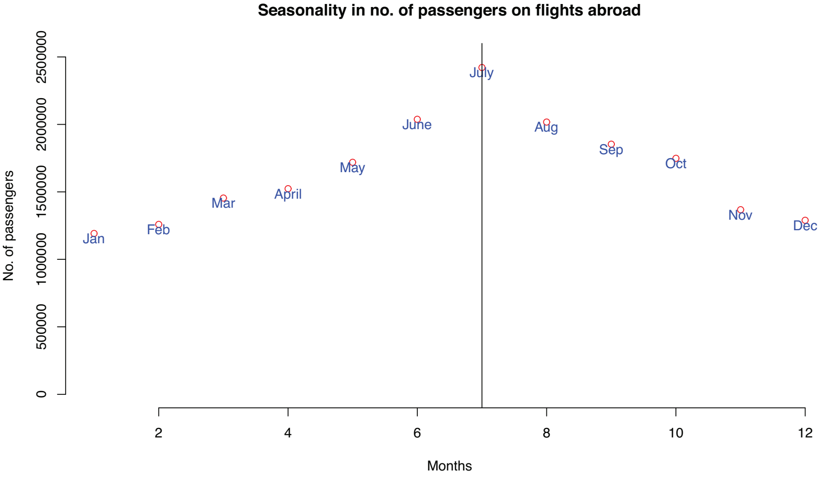

FIGURE 5 Passengers on international flights. Norway, 2015
(Notes: The graph was generated using data on passengers on international flights at Norwegian airports in the year 2015. Statistics can be accessed at avinor.no. The numbers refer to the monthly number of registered travellers on both route and charter flights including transfer passengers and infants (age 0-2).) [Color figure can be viewed at wileyonlinelibrary.com]

month of registration in one given city, Oslo.[19] The red curve represents December. We see that the curve tends to flatten out as the number of days after listing grows. This pattern is consistent with the notion that both new sellers and new (acceptable) bids arrive in smaller numbers in December,

[19] Cities have different survival rates. Thus, I retained Oslo.

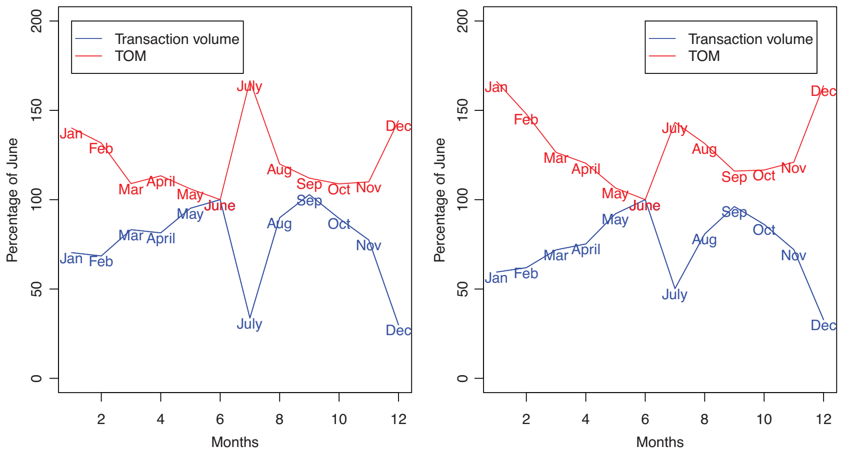

FIGURE 6 Intra-year transaction volume and TOM. Oslo and non-Oslo, 2002-2017
(*Notes*: Number of observations in Oslo: 110,022. Number of observations not in Oslo: 581,170.)
[Color figure can be viewed at wileyonlinelibrary.com]

offering supporting evidence of the notion that there is comovement in volume, listings, TOM, and prices.

This pattern is also in line with Qian (2013), who constructs a model with an optimal stopping problem, in which a seller may postpone a sale. When the sales price is low, the probability of sale postponement is higher. Such a setup allows a mechanism in which sellers that observe that their TOM grows longer self-select into two categories, a category of sell-now sellers and a category of postponing sellers.

In Figure 6, we plot the relationship between transaction volume and TOM, measured as percentages of June for the capital Oslo and the rest of the country. The regularity is clear. When the transaction volume is low, TOM is high, which, again, supports the notion that market activity affects volume, listings, TOM, and prices. It is consistent with Ganduri et al. (2023) who study the effect of liquidity on prices. They exploit a quasi-natural experiment to quantify the effect of liquidity on prices and find that close properties to a bulk-sale experience a price increase of compared to units far away. The analogous mechanism here would be that December is the temporal equivalent of being far removed from a situation characterized with high liquidity, that is, September. It is plausible that the reduction in activity is at the core of the explanation of the December discount and it is consistent with the amplification mechanism suggested in Guren and McQuade (2020). They study the role played by foreclosures in downturns and find that an amplification mechanism accounts for 25% of the reduction in nondistressed prices. In our study, a similar amplification mechanism in December would be started by some sellers who become highly motivated to sell, which in turn could affect prices for all sellers in December.

These observations invite the deeper question of the determinants of market activity itself. Goodman (1993) presents a matching model that incorporates seasonality generated by moving owner-occupiers driven by such factors as school calendar and summer weddings. Harding, Rosenthal et al. (2003) show that families with school-age children have less bargaining power during the summer. Agarwal et al. (2019) use the finding that realtors purchase at a discount to argue that bargaining power is an explanatory factor. They find that one component consists of purchases from sellers who face time pressure. In our study, the relative power between buyers and (some) sellers may change at the end of the year. Caplin and Leahy (2011) construct a model with a feature in which excess supply of houses allows buyers to extract surpluses of sellers. That is consistent with this article's idea that the December discount could be linked to bargaining power between sellers and buyers. For future research, a natural starting point could be to employ the framework of Carillo (2013), which combines list prices, sell prices, and TOMs, to contrast the bargaining power in December and September.

In Norway, temperature levels or light situations could be candidates for explanatory variables since Norway lies at high Northern latitudes. However, both temperature levels and light situations in January are similar to December, yet January has higher market activity and price increases than December. Since weather and temperature would affect both December and January, we should be inclined to search for an exogenous factor that affects December sales but not January sales. One natural candidate is the holiday season and another is the calendar, that is, the end of the year. However, it would be a challenge to separate these two effects as we would find it difficult to separate the dates of the end of the year from the dates of the holidays. I leave it to further research to search for natural experiments that allow the inspection of the (disruption of) holiday patterns to identify the determinants of house price seasonality. This article's main objective has been to document its existence while controlling for composition effects and unobserved heterogeneity.

Finally, let us look at the choice of month. In Norway, there is a sharp drop in prices in July and a sharp increase in prices in January, so an alternative research question could be whether the July, the December, and the January effects are part of an intrayear price pattern caused by the same factors. This article focuses attention on one month, December, rather than two or more months for two main reasons. First, the aim is to substantiate that a between-month price pattern exists and that it is not simply a composition effect. To prove existence, we need only one month, not two. Second, July is typically a vacation travel month compared to its neighboring months, June and August. December, on the other hand, is similar to its neighboring months, November and January, in travel tendencies.[20] Thus, December is a natural starting point to study monthly price effects.

7 | CONCLUSION AND POLICY IMPLICATIONS

There have been reports for some time in Norway that house prices tend to fall in December. I document that this is indeed the case, and rule out that a composition effect can explain all of the price reduction observed in December. However, the estimated December effect is large in a fully specified hedonic model, but is considerably smaller in a repeat-sale model based on log(sell price). The hedonic model of log(sell price) implies a 5% difference, the unit fixed effect models that control for time-varying unobserved heterogeneity yields price differences of 1.3% and 1.5% for ask price and appraisal value controls, respectively.

In order to show that the price reduction is a discount, that is, it amounts to a rebate compared to an identical unit sold earlier in the year, I control for unobserved heterogeneity using a battery of techniques. I use repeat sales to control for time-invariant unit-specific effects, ask prices to account for time-varying unit-specific effects, and appraisal values to handle potential

[20] I have obtained air travel data from avinor.no for the year 2015. Table A.1 shows passengers traveling abroad for each month. July has 20% higher travel frequencies than the second highest months and about twice the traffic in December. December, on the other hand, is lower than November, but higher than January.

seasonality or strategic elements in ask prices. The December discount is intact across specifications and robust to data set changes.

My results indicate that the December price reduction is indeed a discount and that its magnitude is 1.3–1.5% compared to September price levels. The December discount is associated with long TOMs since segmentation of sales into TOM segments implies that the difference between the estimated September coefficient and the estimated December coefficient is reduced or vanishes within same-TOM segments. TOM is not related to unobserved unit effects since a repeat sales, or rather a repeat-TOM, model reveals that there is little persistence between first sale TOM and second sale TOM of the same unit. In other words, the first sale TOM of a given unit does not predict the second sale TOM of the same unit. This observation weakens the position that the December discount is connected to certain units.

There are at least two candidate mechanisms that can generate the December discount. First, the December discount might be caused by extra motivated sellers that have observed nonsuccessful sales through September, October, and November, and seek to secure a sale by offering rebates. Second, the December discount could be caused by low-quality matches between unit attributes and household preferences. Studying discounts across markets by employing a segmentation of Norway into submarkets, we observe that the December discount is larger in submarkets with lower market activity in December. Lower market activity is associated with lower quality matches.

Since the December discount is at around 1.3–1.5% of the price of a house, and since a component of this might be linked to market activity and suboptimal matching, the December discount could be indicative of welfare losses. The evidence is consistent with a search-and-matching idea in which the low prices result from a low number of high-quality matches between buyer preferences and unit attributes. Given such a phenomenon, there could be welfare gains to be made if one sought to arrange housing markets to ensure optimal matching between buyers and units. Potentially, better matching would be achieved either by nudging more sales in low-activity periods or inducing sales in low-activity periods to be moved to high-activity periods. One possibility could be a reduction in the stamp duty in December.

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APPENDIX

TABLE A.1 Ask–appraisal spread and log(ask) regressions—Repeat sales. Listing dates: Norway, 2002–2017.

	Appraisal data	
	Ask-appraisal spread	log(ask)
	I	II
Year FE	YES	YES
Jan-Aug FE	YES (not stat. sign.)	YES, 4 t-values > 2.6
Unit FE	YES	YES
log(app)		0.930 (695)
September	−0.00233** (−3.2)	−0.00171* (−2.3)
October	−0.00200** (−2.8)	−0.00123 (−1.7)
November	0.000456 (0.62)	0.00123 (1.6)
December	0.000196 (0.21)	0.00174 (1.8)
	No. sales = 2	
	N = 111,244	
R^2	0.0251	0.982

Note: The year and calendar month dummies are assigned on the basis of listing date, not sell date. Log(ask) and log(app) denote the logarithm of the ask price and the appraisal value, respectively. Repeat sales data include units that are transacted exactly two times in the 2002–2017 period. FE is short notation for a fixed effect regression run using the plm-function in R and the within-model. Year FE denotes a collection of year dummies (2002 default). Jan-Aug FE denotes a collection of 7-month dummies from January to August, excluding July (default). I report the R^2, not Adj. R^2, due to the high number of constants in FE models. The ask–appraisal spread is computed by taking the difference and dividing by the appraisal value. I use the sandwich and vcovHC functions to obtain robust standard errors, clustered on zipcode, after having demeaned the data. I compute a t-statistic (presented in parentheses) and set the threshold levels for 0.05 (*), 0.01 (**), and 0.001 (***) levels of statistical significance to 1.96, 2.58, and 3.30, respectively, since we have many degrees of freedom.

TABLE A.2 The period between two sell dates on the period between the two ask price dates in a repeat-sales pair, measured in no. days: Norway, 2002–2017.

	Sell date difference
Const.	3.46*** (9.0)
List date difference	0.995*** (5405)
N	213,394
Adj. R2	0.993

Note: The data consist of units that are sold exactly two times. The dependent variable is the number of days between the first and the second sell date. The independent variable is the number of days between the first and the second listing date. The table reports results from a simple OLS regression. I compute a t-statistic (presented in parentheses) and set the threshold levels for 0.05 (*), 0.01 (**), and 0.001 (***) levels of statistical significance to 1.96, 2.58, and 3.30, respectively, since we have many degrees of freedom.

TABLE A.3 Log(sell price) on determinants. Comparison of estimates using two and three repeat sales.

	Two sales	Three sales
Year FE	Yes	Yes
Jan-Aug FE	Yes	Yes
Unit FE	Yes	Yes
log(ask)	0.868*** (544)	0.878*** (375)
log(app)		
Sep	0.00806*** (10)	0.00876*** (8.0)
Oct	0.00495*** (6.1)	0.00395** (3.5)
Nov	0.000302 (0.36)	0.00102 (0.88)
Dec	−0.00482*** (−4.7)	−0.00541*** (−3.9)
No. sales	2	3
No. obs.	213,394	96,525
Adj. R^2	0.885	0.927

Note: The data consist of units that are sold either exactly two times or exactly three times. The results presented for two sales are also presented in Table 4 III, and they are included for comparison purposes. The dependent variable is log(sell price). I use the R-function plm-function to estimate the models. I use the sandwich and vcovHC functions to obtain robust standard errors, clustered on zipcode, after having demeaned the data. I compute a t-statistic (presented in parentheses) and set the threshold levels for 0.05 (*), 0.01 (**), and 0.001 (***) levels of statistical significance to 1.96, 2.58, and 3.30, respectively, since we have many degrees of freedom

TABLE A.4 Regressions of market observations. Market sell–ask spread on market activity in December. Segments of transaction volume. Norway, 2002–2016.

	Transaction data		
	Sell–ask spread. Dec less not December		
Sales volume:	**1–18 (1st quart.)**	**19-91 (2nd/3rd quart.)**	**92-2,973(4th quart.)**
Market activity measure:	**sales**	**sales**	**sales**
Intercept	−0.0381*** (−3.4)	−0.0314*** (−8.3)	−0.0298*** (−9.5)
Rel. Dec. vol.	0.0336 (1.6)	0.0265*** (3.6)	0.0196** (2.8)
No. of markets	65	122	60
Adj. R^2	0.0362	0.0510	0.0427

Note: The regressions were run after partitioning Norway into different markets. First, I removed municipalities with less than 800 transactions in the period. Then, I partitioned each municipality into apartments and nonapartments (detached houses, semidetached houses, and row houses). I also removed transactions from the year 2017 since my records are not complete for this year. Markets with no December transactions were removed. Then, I segmented based on the distribution of sales volume in December. The 25th and 75th percentiles were 18 and 91. For each market, I compute the mean sell–ask spread in December and non-December and the transaction volume in December and non-December. I also compute number of units that were put up for sale in each market (online advertisements) for December and non-December. The for-sale registration date is the date on which the unit was announced for sale on the online platform Finn.no. The variables Relative December transaction volume and Relative December for-sale registration are the number of transactions and registrations in December as fractions of the mean of the other 11 months. Thus, the regressions are the difference between the December spread and non-December spread on the ratio of December activity and non-December activity. The standard errors were computed using the vcovHC-function. I compute a t-statistic (presented in parentheses) and set the threshold levels for 0.05 (*), 0.01 (**), and 0.001 (***) levels of statistical significance to 1.96, 2.58, and 3.30, respectively, since we have many degrees of freedom.