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Thick-Market Effects, Housing Heterogeneity, and the Determinants of Transaction Seasonality*

Plamen T. Nenov, Erling Røed Larsen, and Dag Einar Sommervoll

Abstract

This paper uses cross-sectional variation in transaction seasonality and a search-theoretic framework to develop a test for thick-market effects from matching efficiency. The test relates the extent of transaction seasonality to the degree of horizontal housing heterogeneity. We find a strong positive association between measures of seasonality and housing heterogeneity using a transaction level data set for Norway, which is consistent with the presence of thick-market effects. These results also show that the degree of horizontal heterogeneity of the housing stock is an important determinant of the extent of seasonality in a housing market.

Housing markets are seasonal. In many national and regional markets prices and transaction volumes move in a predictable pattern over a year, a phenomenon widely recognized by real estate agents. However, fewer observers have noted that the extent of seasonality varies systematically across local housing markets.¹ In this paper we use cross-sectional variation in the extent of transaction seasonality to test if thick-market effects from matching

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¹See Section 1 for motivating evidence on these patterns.

efficiency operate in housing markets. In the process we also propose an explanation for the cross-sectional differences in seasonality – the interaction between thick-market effects and horizontal housing heterogeneity.

Thick-market effects from matching efficiency (or thick-market effects, for short) comprise an increase in the probability of transacting from an increase in the number of traders in the market due to improvements in matching efficiency.² The strength of these effects – the extent of the improvement in matching efficiency given more units for sale – depends on the horizontal heterogeneity of the underlying housing stock. Whenever there is little horizontal heterogeneity in the housing stock, i.e. when the willingness to pay for units with the same observable quality varies little among buyers, then buyers have little need to inspect many units for sale in search of the best match to their idiosyncratic tastes. Consequently, an increase in the number of units for sale has only a small effect on match quality. Conversely, if the level of horizontal heterogeneity in a housing market is large, buyers have to inspect many housing units to find a better match, and so an increase in the number of units for sale could improve match quality substantially. Therefore, if thick-market effects are present in the housing market, they are stronger in markets with more heterogeneous housing units than in markets with a more homogeneous housing stock.

We formalize this idea in a simple search-theoretic model of the housing market. We model horizontal heterogeneity as the dispersion in the valuations of different buyers for the same unit, so that a higher dispersion in buyer valuations corresponds to a market with greater horizontal heterogeneity.³ In this framework, we show that variations in the stock of houses for sale produce a larger response in transaction volume in markets with more horizontal heterogeneity. Therefore, one expects to observe greater transaction seasonality – for example, due to small seasonal variations in the stock of houses for sale – in housing

²The notion of thick-market effects from matching efficiency was first introduced in Diamond (1981) in the context of a frictional labour market. Ngai and Tenreyro (2014) are the first to introduce that mechanism in the context of the housing market.

³Although we present our framework in the context of the housing market, the insights of our theoretical model apply more broadly to other market characterized by search frictions and horizontal heterogeneity.

markets with greater horizontal heterogeneity. We proceed to test this prediction of our theoretical framework.

Our empirical strategy uses variation across housing markets to test for a positive relationship between housing heterogeneity and the extent of transaction seasonality. We examine housing markets partitioned by geography (in the form of Norwegian municipalities) and by housing type (apartments vs. houses), and size (defined by the number of bedrooms) within each geographic segment.

We construct measures of the extent of seasonality, both for transaction volumes and for a proxy for the average probability of transacting for a seller. Additionally, we consider seasonality in median time-on-market (TOM). Since housing units of different type and size differ according to their degree of horizontal heterogeneity, we compare directly the seasonality of different type-and-size groups within the same municipality. Additionally, we measure the degree of horizontal heterogeneity in a market via the residual price variation from hedonic regressions. This measure is motivated by the following observation: in the presence of a frictional search and matching process, buyers are not always able to match with their most preferred housing unit. The degree of mismatch between a buyer and the house he ends up acquiring affects the transaction price and leads to price variability even among observationally equivalent objects. The greater the degree of horizontal heterogeneity, the higher the price variability.

We apply our empirical methodology to a unique housing transaction data set for Norway. The data set we use is particularly suitable for such analysis since it includes exact property listing and sale dates. We first show that within municipalities, more heterogeneous groups such as larger houses are also more seasonal compared to less heterogeneous groups such as smaller apartments. Second, there is a strong positive and statistically significant association between our measures of horizontal heterogeneity and seasonality. Specifically, for a sub-market that scores one standard deviation higher on our heterogeneity measure, transaction volume increases by 4.4 percent more for each percentage point increase in the number of

houses for sale. Similarly, the seller transaction probability increases by 8 percent more. The positive relation between heterogeneity and seasonality holds after controlling for both fixed municipality and type/size group characteristics. We interpret these results as evidence that thick-market effects are important for the housing market and that horizontal housing heterogeneity is a determinant of transaction seasonality differences in the cross-section.

Our paper contributes to the growing literature on search-based models of the housing market.⁴ It is closely related to the seminal contribution of Ngai and Tenreyro (2014), who argue that thick-market effects are important for explaining the substantial seasonal variation in housing transactions and prices observed in US and UK data. When thick-market effects are sufficiently strong, they amplify the impact of deterministic seasonal variation in the number of buyers and sellers on transactions and prices. The authors provide evidence for this mechanism from the American Housing Survey by examining several proxies for the quality of matches between buyers and houses for transactions that occur in the second or third quarter vs. the rest of the year. They conclude that matches made in the “hot” season are of higher quality. Also, a calibrated version of their model can quantitatively account for the observed aggregate time-series pattern in the US and UK.

We complement this important study in two ways. First, we show theoretically that thick-market effects from matching efficiency are stronger in markets where match quality considerations are more important. To this end, the framework we study explicitly models the level of horizontal heterogeneity in a market. In contrast, Ngai and Tenreyro do not explicitly model the degree of horizontal heterogeneity but implicitly assume that it is sufficiently large, so that thick-market effects have large amplification effects on transaction volume. Consequently, the cross-sectional predictions of our framework are independent of the *overall* strength of thick-market effects and only depend on their *relative* strength across markets. Secondly, we develop a test for thick-market effects in the housing market based on the

⁴A non-exhaustive list of contributions includes Wheaton (1990), Krainer (2001), Novy-Marx (2009), Piazzesi and Schneider (2009), Genesove and Han (2012) Diaz and Jerez (2013), Anenberg and Bayer (2013), Ngai and Sheedy (2014), and Moen *et al.* (2014), among others. See Rocheteau and Weill (2011) for an overview of search and matching models applied to asset markets, including housing markets.

predictions of our framework and find empirical evidence for this prediction using our detailed housing transaction data.

In its focus on thick-market effects from matching efficiency the paper is also related to a labour-search literature that deals with this issue (Diamond, 1981; Petrongolo and Pissarides, 2006; Gautier and Teulings, 2009). Specifically, our framework and empirical methodology can be applied to test for thick-market effects in other frictional markets with seasonal effects, such as the labour market.⁵

Several other authors have documented seasonality in housing markets. Case and Shiller (1989) and Hosios and Pesando (1991) are the first to document such seasonality in repeat-sales house price indices for Chicago and Toronto, respectively. Goodman (1993) documents that geographic mobility in the US is also highly seasonal, a pattern which he explains via coordination effects in the housing market. More recently, Røed Larsen and Weum (2008) find seasonality in house prices in the Norwegian aggregate housing market using a repeat-sales index. Kaplanski and Levy (2012) examine seasonality in house prices in the US, UK, and Australia.

The rest of the paper is organized as follows. In the next section, we present several empirical patterns that motivate our analysis. Section 2 contains the theoretical framework that informs our empirical strategy. Section 3 describes our empirical strategy and the specific variables we construct. Section 4 describes our data and presents our empirical findings. Section 5 provides a short discussion of the results, confounding effects, and robustness tests. Section 6 concludes.

1 Motivating Empirical Patterns

We begin with a few empirical patterns that motivate our analysis. Figure 1 shows the extent of seasonality in transactions and prices for the Norwegian housing market in 2011.

⁵See Barsky and Miron (1989) for evidence on seasonal cycles in the U.S. economy and labour market.

Both prices and volumes follow a common seasonal pattern.⁶ However, while seasonal price fluctuations tend to be around 1%, seasonal fluctuations in transaction volume are typically more than 50%.⁷

[Figure 1]

Looking further into the seasonality of transaction volume, Figure 1b plots the same seasonal pattern in volume together with a monthly series for the seasonal fluctuations in the seller probability of transacting and the aggregate stock of housing advertisements in 2011. Importantly, transaction volume does not respond one-for-one to changes in the stock of houses for sale. Instead there is an amplified response of volume to seasonal fluctuations in the for-sale stock. This amplified response arises from the contemporaneous response of the seller probability of transacting.

Finally, an aggregate seasonality pattern hides potentially substantial differences in the extent of seasonality across different housing markets. For example, in Figure 2 we show the transaction seasonality for two Norwegian municipalities, Bærum, and Skien, for each month in 2011. The temporal profile for each of these housing markets follows a similar pattern as the aggregate pattern in Figure 1. However, transaction seasonality is much more pronounced in Bærum compared to Skien.

[Figure 2]

Why is there an amplified response in transactions to variations in the stock of houses for sale? Also, why are there differences in this response across housing markets? As discussed

⁶Unlike the US and UK, the aggregate seasonal pattern in Norway is characterized by a pronounced dip in the summer (i.e. July). This difference in the temporal pattern of seasonality likely stems from differences in the holiday calendar in Norway compared to the UK and US with the majority of people taking vacations in July in Norway.

⁷The small seasonal variations in prices compared to volume motivates our empirical focus on cross-sectional differences in volume later on.

in the Introduction, thick-market effects from matching efficiency can provide an answer to the first question. In this paper we show that thick-market effects can provide an answer to the second question, as well. In the next section we demonstrate in a simple theoretical framework that the extent of seasonality due to thick-market effects depends on the degree of horizontal heterogeneity in a market. We then test for this cross-sectional prediction using a detailed transaction-level data set.

2 Theoretical Framework

Houses are heterogeneous. They vary in observable hedonics, such as size and number of bedrooms. Some of these variables naturally partition the housing market into submarkets. Potential buyers self-select into these submarkets (for example, because they are looking for an apartment or a house) and have common valuations *ex ante*. We label differences along these *ex ante* observable characteristics as vertical heterogeneity. However, houses also vary in characteristics that cannot be listed in ads, nor are easy to quantify, and which can only be observed upon inspection. Potential buyers have heterogeneous preferences and idiosyncratic valuations over such characteristics. We call differences along these *ex post* observable characteristics horizontal heterogeneity. The presence of such characteristics necessitates a costly search and matching process.

The horizontal heterogeneity of the housing stock implies that having more units for sale leads to higher quality matches, since buyers are able to choose from a larger set of houses. The more (horizontally) heterogeneous a given housing market, the more important it is for match quality and successful transactions to have more units for sale. In this section we formalize this idea in a simple equilibrium model of the housing market that features a frictional search process, (*ex post*) heterogeneity in preferences over housing units, and thick-market effects from matching efficiency. The implications of this model provide the basis for our empirical strategy.⁸

⁸In the model only horizontal heterogeneity will be at play, as we assume buyers self-select and search in

There is a measure b of buyers and measure s of housing units for sale initially owned by sellers. All agents are risk neutral and have transferable utility. Buyers demand a single unit of housing, and sellers hold a single unit for sale. Buyers and sellers meet according to a frictional search process in multiple meeting stages. The number N_s of sellers a buyer meets within the period follows a Poisson distribution with parameter $q(b, s)$. Therefore, $q(b, s)$ can be interpreted as the expected number of viewings by a buyer. We assume that q is strictly increasing in s and continuously differentiable in both arguments.⁹

Buyers have idiosyncratic tastes over housing units, or equivalently, there is horizontal heterogeneity in housing. Buyers do not know *ex ante* which units are more preferable but obtain this information only on inspection of the units for sale. Specifically, upon meeting with a seller, a buyer observes an idiosyncratic match quality of \mathcal{U} , which gives the gross utility he would derive from that particular housing unit. We assume that

$$\mathcal{U} = U - u, \tag{1}$$

where $U > 0$ is the buyer's gross utility if he is perfectly matched with a housing unit and u is a stochastic "mismatch" discount. For tractability, we assume that u follows an exponential distribution with mean $\sigma > 0$.

The parameter σ naturally determines the degree of horizontal heterogeneity of the housing stock. A higher value of σ implies that different buyers have valuations of the same unit that are more dispersed. Equivalently, a single buyer has more dispersed valuations of different housing units.¹⁰

the most attractive submarket (defined by *ex ante* observables).

⁹We also assume that $q(b, s)$ is sufficiently low for any b and s , so that the total number of transactions never exceeds the stock of houses for sale, s . Finally, we assume that N_s gives the total number of meetings between a buyer and sellers, in which the buyer does not face direct competition from other buyers for his most preferred unit. Thus, we disregard cases in which one seller will be bargaining with more than one buyer, which can easily occur when a seller is assumed to meet with more than one buyer (Albrecht *et al.* (2006), Galenianos and Kircher (2009), and Albrecht *et al.* (2014)). Though realistic, an analysis of such types of meetings is beyond the scope of this paper.

¹⁰As an example, consider the following two fictional local housing markets. In one housing market the housing units are completely identical (adjusting for quality) in having the same floor plan, interior decorations, etc.. In that market, agents do not have heterogeneous preferences over different housing units. Using

At the end of the period, each buyer considers the unit with the highest match quality from the sequence of draws he has made. For example, a buyer i with n idiosyncratic draws $\mathcal{U}_j = U - u_j$, for $j \in \{1, 2, \dots, n\}$, considers a unit with match quality $\mathcal{U}^* = \max \{\mathcal{U}_1, \mathcal{U}_2, \dots, \mathcal{U}_n\}$, or equivalently, the unit with $u^* = \min \{u_1, u_2, \dots, u_n\}$. Given match quality \mathcal{U}^* , the buyer bargains over the transaction price with the seller of the unit, which delivers this match quality. Trading takes place only if the surplus from trade is non-negative. If that is the case, a buyer and a seller split the surplus according to symmetric Nash bargaining. If a buyer does not meet a seller or does not transact, he obtains a payoff of $U_0 < U$. If a seller fails to transact he obtains a payoff that is normalized to 0. Therefore, trading takes place, iff $\mathcal{U}^* - U_0 \geq 0$, or equivalently, $u^* < u_0 \equiv U - U_0$, and the transaction price in that case is $p(u^*) = 0.5 (U - u^* - U_0)$.

Since there is trade for $u^* < u_0$, if $H(x; b, s, \sigma)$ denotes the fraction of buyers with $u^* < x$ at the end of the period, then transaction volume is given by

$$TV \equiv A(b, s, \sigma) b, \quad (2)$$

with

$$A(b, s, \sigma) \equiv H(u_0; b, s, \sigma), \quad (3)$$

This means that the *ex ante* probability of transacting for a seller is

$$TP \equiv \frac{TV}{s} = A(b, s, \sigma) \frac{b}{s}. \quad (4)$$

Therefore, $A(b, s, \sigma)$ can be interpreted as the efficiency of matching between a buyer and a seller in a framework in which total transaction volume is determined by a matching function $\tilde{M}(b, s, \sigma) = A(b, s, \sigma) b$. However, rather than being exogenous, in our framework, matching the notation in our model, this would be a market with $\sigma \rightarrow 0$, and so a buyer is perfectly matched with the first housing unit he samples. In the other housing market, housing units differ substantially in their layout. In that market, some agents may prefer one housing unit over another, because of the particular set-up of its living space. In that case a buyer needs to sample multiple units to find the best match. Therefore, in this market, the value of σ is large.

efficiency $A(b, s, \sigma)$ is endogenous. It depends on the number of buyers and sellers and on housing heterogeneity parametrized by σ .

Thick-market effects from matching efficiency originate from the dependence of matching efficiency on the number of traders in the market. Specifically, as we show in the Appendix, in our framework, $A(b, s, \sigma)$ is increasing in the number of units for sale, s , since the number of expected viewings for a buyer, q , is increasing in s . A higher number of viewings, on the other hand, increases the likelihood that the buyer is better matched with the housing unit he ends up considering. Therefore, a greater number of units for sale improves matching efficiency and increases the probability of a transaction taking place.

Our theoretical framework implies that there is an interaction effect between s and σ , so that $(d \log A / d \log s)$ is increasing in σ .¹¹ Therefore, in a housing market with greater heterogeneity (higher value of σ), matching efficiency is more responsive to changes in the for-sale stock. What this means is that the elasticity of both transaction volume $(d \log TV / d \log s)$, and seller transaction probability $(d \log TP / d \log s)$ to variations in the stock of houses for sale, depends monotonically on housing heterogeneity σ . We summarize this observation in the following

Proposition 1. *In the housing market model above, the elasticities $(d \log TV / d \log s)$ and $(d \log TP / d \log s)$ are increasing in the level of horizontal housing heterogeneity parametrized by σ .*

Proof. See Appendix. □

The intuition for this result is straightforward. Whenever the housing stock is more heterogeneous (σ is higher), i.e. buyers valuations are more dispersed, sampling from a larger number of objects has a stronger impact on buyers' probability of finding the "right house" and hence on matching efficiency.

¹¹The function $A(b, s, \sigma)$ is log-supermodular in s and σ (see Athey (2002)). The property of log-supermodularity is what drives our main theoretical result in Proposition 1 below.

It is important to note that this result is independent of the strength of thick-market effects, as long as they are present (i.e. as long as $(\partial A/\partial s) > 0$). If thick-market effects are sufficiently strong, they can amplify the response of transaction volume to variations in the for-sale stock.¹² In that case, the seller transaction probability and the for-sale stock co-move positively as in Figure 1b.

However, even if there is no amplification, Proposition 1 would still hold. In other words, the cross-sectional predictions of our framework are independent of the *overall* strength of thick-market effects and only depend on their *relative* strength across markets.

In the case in which thick-market effects through matching efficiency are absent, so that A does not depend on b and s , the interaction effect between s and σ , on which Proposition 1 depends, will not be present either. Consequently, a positive association between horizontal heterogeneity in a housing market and the elasticity of transaction volume (and seller transaction probability) to the stock of houses for sale (or the seasonality in transactions across markets) is consistent with thick-market effects operating in the housing market. Therefore, the core of our empirical strategy below is to test for such an association.

3 Empirical Strategy

In this section we describe our strategy for testing the predictions of our theoretical framework. We start by describing how we define individual housing markets, the units of observation in our empirical analysis. We then explain how we construct our measures of seasonality and horizontal housing heterogeneity for each of these individual housing markets.

¹²By “strong” thick-market effects we mean that the derivative $(\partial A(b, s, \sigma)/\partial s)$ is sufficiently large in magnitude, so that $(\partial TP/\partial s) > 0$. In our framework this is ensured by $(\partial q/\partial s) > 1$. Formally, there is amplification of transaction volume TV from changes in the for-sale stock s whenever the elasticity $(d \log TV/d \log s) > 1$, so a 1% increase in s increases transaction volume by more than 1%. Since $TV = sTP$, this elasticity is

$$\frac{d \log TV}{d \log s} = \frac{d \log TP}{d \log s} + 1,$$

so there is amplification whenever $(d \log TP/d \log s) > 0$.

3.1 Defining Housing Markets

Following our theoretical framework, we are interested in analysing the behaviour of housing markets that contain housing units that are (*ex ante*) observationally similar. Nevertheless, a perfect segmentation of housing markets into small segments with *ex ante* identical units is not possible in practice, since it leads to markets that are too small and too noisy for empirical analysis or introduces mis-classification biases. Given these constraints, we define housing markets in the following way. First, we partition along a spatial dimension. We focus on Norwegian municipalities as well as the city districts of the four largest cities (Oslo, Bergen, Trondheim, and Stavanger).¹³ We refer to these collectively as municipalities. Second, we partition each municipality along a housing type/size dimension. We define 6 type/size groups: apartments, subdivided into small (1 bedroom or less), medium (2 bedrooms), and large (3 or more bedrooms), and houses, subdivided into small (2 bedrooms or less), medium (3 bedrooms), and large (4 or more bedrooms). Therefore, our unit of observation is a housing market of a particular housing type/size group within a municipality.¹⁴

3.2 Measures of Seasonality in Transactions

3.2.1 Measure of seasonality using transaction volumes

We first measure seasonality using transaction volumes. We map the extent of seasonality in an individual market to a “beta” - the regression coefficient of a time series regression of local transaction volumes on aggregate transactions. The idea motivating the use of this measure is that it captures the sensitivity of the (monthly) transaction volume in a market relative

¹³City districts are treated separately in statistical products supplied by the Norwegian statistical agency and also differ in the composition of their households by size, age and income.

¹⁴We view the segmentation of the housing market along these three dimensions - geography, type, and size - as appropriate and consistent with the search behaviour of households. As Piazzesi *et al.* (2013) show using the observed search behaviour of households in San Francisco, there is a natural segmentation in search behaviour along a geographic dimension and a price/size dimensions. In the case of the U.S. size search is over the number of bathrooms in a housing units. For Norway, anecdotal evidence indicates that household searches tend to be based on the number of bedrooms rather than bathrooms. Alternative segmentation produces similar results, as we show in the Online Supplement.

to the time variation in the aggregate transaction volume. A value above 1 implies that the market is more seasonal than the aggregate, while a value below 1 implies that the market is less seasonal than the aggregate.

We implement this “transaction volume beta” (“TV beta” for short) by estimating the following regression

$$\log TV_{g,m,t} = \alpha_{g,m} + \beta_{g,m}^{TV} \log \overline{TV}_{-m,t} + P_5^{g,m}(t) + \eta_{g,m,t}, \quad (5)$$

where $TV_{g,m,t}$ denotes the transaction volume in market (g, m) , and month t , where g denotes a housing type/size group, and m is a municipality. Similarly, $\overline{TV}_{-m,t}$ is the aggregate transaction volume in all other municipalities excluding municipality m . Finally, $P_5^{g,m}(t)$ denotes a 5th degree polynomial time trend, and $\eta_{g,m,t}$ is a stochastic disturbance term with zero mean.

3.2.2 Measure of seasonality using transaction probabilities

We derive an alternative measure of seasonality by considering seller transaction probabilities instead of transaction volumes. Although we do not directly observe the average probability of transacting for a housing unit for sale, if we can observe the stock of houses for sale for each segment, we can make an estimate of that average probability. Fortunately, our data set allows us to create a proxy for the stock of houses for sale in a given month that closely tracks the true for-sale stock. Specifically, starting from some initial condition v_1 , we construct the stock of houses for sale at the beginning of month $t > 1$, v_t , recursively by

$$v_t \equiv v_{t-1} + n_{t-1} - TV_{t-1} \quad (6)$$

where n_{t-1} is the number of newly listed properties and TV_{t-1} is the number of sales during the previous month.¹⁵

¹⁵To reduce the effect of the initial condition v_1 we drop the first 24 months in the constructed stock of houses for sale series. Similarly, since we observe only sold properties in our data set, to remove the effect

Given this series, we follow the labour-search literature (Shimer (2012)) and construct an average seller transaction probability for market (g, m) (municipality m and type/size group g) in month t , $TP_{g,m,t}$, which satisfies

$$TP_{g,m,t}v_{g,m,t} + Q_{g,m,t} = TV_{g,m,t}, \quad (7)$$

where $v_{g,m,t}$ is the stock of units for sale at the beginning of month t , $TV_{g,m,t}$ is the transaction volume in month t and $Q_{g,m,t}$ is the number of units that are listed within month t and also sell in month t .¹⁶ Solving for $TP_{g,m,t}$, we get:

$$TP_{g,m,t} = \frac{TV_{g,m,t} - Q_{g,m,t}}{v_{g,m,t}}. \quad (8)$$

We then regress (the log of) that transaction probability measure on the aggregate transaction probability in month t , constructed in the same way. Thus, the “transaction probability beta” (or “TP beta” for short) is the regression coefficient from the following regression:

$$\log TP_{g,m,t} = \alpha_{g,m}^p + \beta_{g,m}^{TP} \log \overline{TP}_t + P_5^{p,g,m}(t) + \eta_{g,m,t}^p, \quad (9)$$

where $TP_{g,m,t}$ denotes the transaction probability in market (g, m) and month t , \overline{TP}_t is the aggregate transaction probability in month t , and $\eta_{g,m,t}^p$ is a mean zero disturbance term.

The interpretation of $\beta_{g,m}^{TP}$ as a measure of seasonality is the same as with the TV beta, $\beta_{g,m}^{TV}$.

of not observing all listed properties towards the end of the sample period we drop the last 7 months in the constructed housing stock series. This leaves us with 96 monthly observations for the stock of houses for sale between 2004 and 2011, which we use in the subsequent analysis. Since we observe only sold properties, differences may arise from unsold units being withdrawn from the market. In the Supplementary Materials we show that our constructed series of houses for sale at the aggregate level is highly correlated with the stock of active advertisements, which is the true stock of units for sale. Unfortunately, the stock of active advertisements is only available at the national level so it cannot be used directly in our empirical investigation.

¹⁶The necessity to account for $Q_{g,m,t}$ arises from the fact that in a longer time period (such as a month) the assumption that new units that are listed do not sell within the period is too strong and would bias the estimated transaction probability. See Shimer (2012) for a discussion of this bias from time aggregation in the context of estimating job finding probabilities in labour markets.

3.2.3 Transaction volume (and probability) elasticity

Our next two measures rely directly on Proposition 1, and hence are contingent on our matching model of the housing market. Specifically, we estimate the elasticity of transaction volume and average transaction probability to the stock of houses for sale, denoted by

$$\epsilon_{g,m}^{TV} \equiv \frac{d \log TV_{g,m}}{d \log v_{g,m}} \quad (10)$$

and

$$\epsilon_{g,m}^{TP} \equiv \frac{d \log TP_{g,m}}{d \log v_{g,m}}. \quad (11)$$

Though not a measure of seasonality *per se*, Proposition 1 implies that in the presence of thick-market effects, there should be a monotonic ranking of these elasticities with respect to the horizontal heterogeneity of the housing stock in a housing market. Also, there is a link between the degree of seasonality in transactions in a market and these elasticities. A higher value of these elasticities implies that variations in the housing stock are amplified to a greater extent, and so are associated with more seasonal transaction volumes.

Similar to (5) and (9) we estimate these elasticities by controlling for a polynomial time trend. Specifically, for $\epsilon_{g,m}^{TV}$ we estimate the following model:

$$\log TV_{g,m,t} = \alpha_{g,m} + \epsilon_{g,m}^{TV} \log v_{g,m,t} + P_5^{g,m}(t) + \eta_{g,m,t}, \quad (12)$$

where as in (5) $TV_{g,m,t}$ is transaction volume in market (g, m) and month t and $v_{g,m,t}$ is the stock of houses for sale in that market and time period.

3.2.4 A measure based on time-on-market (TOM)

We use information on the listing and sales dates of properties to create a measure of seasonality in the median seller time-on-market (TOM) for housing units, i.e. a TOM beta. Although not a direct implication of our static framework, the behaviour of TOM and the

seller transaction probability are related.¹⁷ However, a time-on-market measure of seasonality would not be affected by biases in the measured stock of houses for sale, which can be a problem for the transaction probability measure.

Formally, we construct the TOM beta from the estimation of the following model

$$\log TOM_{g,m,t} = \alpha_{g,m} + \beta_{g,m}^{TOM} \log TOM_{g,t} + P_5^{g,m}(t) + \eta_{g,m,t}^{TOM}, \quad (13)$$

where $\log TOM_{g,m,t}$ is the log of the median time-on-market for properties sold in month t in submarket (g, m) , $\log TOM_{g,t}$ is the log of the median time-on-market for properties in group g sold in month t , $P_5^{g,m}(t)$ is a 5th degree polynomial time trend, and $\eta_{g,m,t}^{TOM}$ is a mean zero noise term.

3.3 Measure of Horizontal Heterogeneity

We construct a measure of horizontal heterogeneity based on a prediction of our theoretical framework regarding the variability of transaction prices in markets with different levels of horizontal heterogeneity. In an environment with search frictions and idiosyncratic match quality, buyers are not always able to match with their most preferred housing unit. This mismatch leads to equilibrium price dispersion even among observationally equivalent housing units.¹⁸ The larger the horizontal heterogeneity, or equivalently, the larger the variance of idiosyncratic match quality, the larger the equilibrium price dispersion.

We illustrate this property for a special case of our framework in Section 2. Let $Var(p_i; \sigma)$ be the variance of transaction prices p_i observed in a market with horizontal heterogeneity parametrized by σ . We then have the following

Proposition 2. *For the housing market model described in Section 2, consider the limit*

¹⁷In fact, in a dynamic model with search-and-matching frictions and a constant per-period seller transaction probability, the average time-on-market equals the reciprocal of the per-period transaction probability.

¹⁸This type of price dispersion due to matching frictions is similar to the wage dispersion that arises in the labour market due to search frictions (e.g. Burdett and Mortensen (1998)), and which has been shown to be a substantial component of overall wage variability (Postel-Vinay and Robin (2002)).

economy with $u_0 \rightarrow \infty$. Then $\text{Var}(p_i; \sigma)$ is monotonically increasing in σ .

Proof. See Appendix. □

Proposition 2 shows a one-to-one mapping between the horizontal heterogeneity of the housing stock and the price variability arising from the interaction of horizontal heterogeneity and the search frictions.¹⁹ A market with higher horizontal heterogeneity (higher σ) has larger price variability for observationally equivalent units. Therefore, one can use this price variability as a proxy for the degree of horizontal heterogeneity in a market.

We measure this price variability as the residual standard deviation from a set of hedonic regressions that control for observable differences between housing units. We denote this measure by $\sigma_{g,m}^p$ for group g and municipality m . We estimate hedonic regressions for each municipality and include covariates for property type, size, age, number of bedrooms, location indicators given by postal codes, and interactions between them.²⁰ Additionally, we include a flexible time trend given by month fixed effects. The adjusted R^2 coefficients from these regressions are very high, with a median of around 0.86. In the Supplementary Material we report all the covariates and the distribution of (adjusted) R^2 coefficients.

Using residual price variability as a proxy for horizontal heterogeneity has important caveats. Even with a rich set of covariates and interactions, the hedonic regressions are not able to control for all vertical housing characteristics. These include unobserved attributes that are observable to buyers, such as the maintenance condition of a property or upgrades by previous owners. Such vertical attributes would account for part of the residual price variability. Therefore, our use of residual price variability as a proxy for horizontal heterogeneity rests on the assumption that any residual vertical heterogeneity in a housing market is independent of the degree of horizontal heterogeneity.

¹⁹It can be shown numerically that this property holds away from the limit $u_0 \rightarrow \infty$.

²⁰Postal codes provide the lowest level of geographic aggregation in our data set. In practice, postal codes in Norway identify narrow geographic locations. For example, the average population of individuals associated with a postal code in the 123 municipalities that we consider is 2130.

3.4 Inferences and Tests

We conduct two sets of tests. First, we make a direct comparison of seasonality patterns across housing type/size groups via a set of pairwise tests. Second, we use price variability as a proxy for horizontal heterogeneity to test for a positive association with seasonality.

3.4.1 Group comparison

First, we compare the seasonal behaviour of the 6 different housing type/size groups. The reasoning for performing a direct group comparison of seasonality is that different groups have different levels of horizontal heterogeneity due to the fundamentally different nature of housing units within each group. For example, a one-bedroom apartment tends to be relatively standardized with a limited variability in floorplans across units, outdoor amenities, and non-observable attributes. At the other extreme, even observationally similar (size, age, bedrooms, etc.) large houses tend to be diverse in terms of floorplan, garden, surroundings, and the whole architecture of the house. Therefore, if groups could be ranked relative to one another in terms of the degree of horizontal heterogeneity, it would be possible to examine whether lower ranked groups are also less seasonal or not. Additionally, a direct group comparison of seasonality is robust to the caveat discussed in Section 3.3 regarding the use of price variability as a proxy for horizontal heterogeneity.

To make such comparisons we conduct a number of pairwise statistical tests of our seasonality measures, i.e. group 1 vs. group 2, group 1 vs. group 3, etc. We also compare groups in terms of price variability to confirm if our priors about the heterogeneity rankings of different groups, as illustrated by the examples above, hold. We construct test statistics using only the variation within municipalities (i.e. we control for municipality fixed effects).

We implement these tests in the following way. For each group g and measure y we estimate the following fixed-effects regression:

$$y_{g,m} = \gamma_g + \delta_m + \eta_{g,m} \quad (14)$$

where m denotes a municipality, γ_g is the coefficient on the indicator variable for group g , δ_m is a municipality fixed effect and $\eta_{g,m}$ is a mean zero noise term. We then test a set of hypotheses of the form $H_0 : \gamma_{g_i} \leq \gamma_{g_j}$, where g_i and g_j are distinct groups ($i, j = 1, 2, \dots, 6$, and $i \neq j$). Given the six groups we work with, there are 15 unique pairwise comparisons of this type. Finally, we use a Bonferroni method to test each hypothesis at an overall significance level of 5%.²¹ The results of this test are presented in Section 4.1.

3.4.2 Regression analysis

We next turn to a regression analysis of the link between price variability and seasonality. We estimate the following fixed-effects model:

$$y_{g,m} = \alpha \sigma_{g,m}^P + \delta_m + \eta_{g,m}, \quad (15)$$

where $y_{g,m}$ is a measure of seasonality for market (g, m) (group g and municipality m), $\sigma_{g,m}^P$ is price variability (our horizontal heterogeneity measure), δ_m is a municipality fixed effect and $\eta_{g,m}$ is a mean zero error term. As discussed in Section 2, thick-market effects from matching efficiency imply that the coefficient α has a positive value.

We finally estimate a model with both municipality and type/size group fixed effects where we examine the relation between price variability and our seasonality measures using only variation within municipalities and groups. We estimate the following model

$$y_{g,m} = \alpha \sigma_{g,m}^P + \gamma_g + \delta_m + \eta_{g,m}, \quad (16)$$

²¹The Bonferroni method is the most conservative approach to constructing p-values for tests of multiple hypotheses. Given an overall significance level of α^* and a number n of tests, the Bonferroni method rejects a particular null hypothesis if the p-value from the test is lower than $\alpha = \frac{\alpha^*}{n}$.

where $y_{g,m}$, $\sigma_{g,m}^P$ and, δ_m are as before and γ_g is a (type/size) group fixed effect.

Including municipality and group fixed effects allows us to control for potential confounding effects arising from the demand side of the market, as we discuss in Section 5. Section 4.2 presents the results of these tests.

4 Data and Empirical Results

Our data set contains 803,430 observations of housing transactions in the period 7 January 2002 – 5 July 2012 for Norway obtained from the housing data firm Eiendomsverdi. The data set consists of all market-based (realtor-mediated and advertised) housing transactions in that period, as well as hedonic variables, a geographic location, transaction price, property listing date, and actual sale date. The Supplementary Material contains additional information on the data and explains our data truncation procedure.

We use this transaction level data set to construct the variables described in Sections 3.2 and 3.3. Table 1 provides summary statistics for all of these constructed variables. We study municipalities with at least 1000 total transactions in our sample. This yields 123 spatial markets. Each municipality is partitioned into 6 housing type/size submarket groups. We examine submarkets with at least 100 transactions giving us a total of 647 submarkets. Inspecting Table 1 reveals that there is substantial variation in our seasonality measures across submarkets.²²

[Table 1]

Table 2 shows the raw correlations between our constructed variables. Examining this table, we observe a positive correlation between seasonality and heterogeneity (first column). Additionally, the different seasonality measures generally tend to be positively correlated among each other.

²²The submarket level data used in the empirical analysis is available online on the journal’s website.

[Table 2]

We turn now to a more detailed analysis of the link between heterogeneity and seasonality.

4.1 *Group Comparison*

Table 3 presents the results from the estimation of equation (14). It tabulates the difference in the seasonality measures (columns 2 to 6) for each group relative to the group of small (1 bedroom or less) apartments. It also contains the difference in price variability (column 1). We observe increasing estimates as we proceed downward along each column. This is evidence of a ranking between groups in terms of housing heterogeneity, which supports the conjecture that different housing type/size groups differ in terms of horizontal heterogeneity. There is a similar ranking in terms of seasonality. In particular, markets with larger objects tend to be more seasonal while houses tend to be more seasonal compared to apartments. For example, medium-sized and large apartments tend to be more seasonal along a number of measures compared to small apartments. Medium-sized and large houses tend to be more seasonal than apartments of any size.

[Table 3]

We corroborate these observations when we examine the results from the set of pairwise statistical tests given in Table 4. Specifically, using the TV beta measure, 11 out of 15 pairs are rejected at an overall significance level of 5%. For our other measures the rejection rate is lower but comparable. Overall, the strongest rejection tends to occur for the groups of medium-sized and large houses, which appear to be substantially different in their seasonality patterns from the other groups. The former are also the groups with the substantially large measures of heterogeneity.

The comparison across groups points to a clear ranking in terms seasonality. Small apartments tend to be the least seasonal, while medium and large houses are the most seasonal.

[Table 4]

4.2 Regression Analysis

Table 5 presents the results from regression equation (15). The coefficients are positive and strongly significant for each measure. A housing market with a more heterogeneous housing stock, as proxied by residual price variability, therefore, tends to have a stronger seasonal pattern.

To get a sense of the magnitude of these estimates, consider the coefficients for the TV and TP elasticities, which give us the absolute differences in the extent of seasonality across housing markets with different degrees of horizontal heterogeneity. Specifically, consider two housing markets, A and B, with market B scoring one standard deviation higher in residual price variability compared to market A. This difference between the two markets implies that they differ in terms of TV and TP elasticities by around 0.044 and 0.081, respectively.²³ Thus, transaction volume in market B increases by 4.4% more than in market A when the stock of houses for sale increases by 1 percentage point. Transaction probability increases by 8.1% more.

[Table 5]

Table 6 presents the results for the estimation of equation (16). As the table shows, most of the regression coefficients are still positive and statistically significant after including group fixed effects. The only coefficient that is not significant is the coefficient on TV elasticity, although it is still positively estimated. The other coefficients have lower magnitudes than

²³We obtain these numbers by multiplying the respective coefficient estimates from Table 5 by the standard deviation of price variability, which is 0.032.

the estimates from equation (15) (apart from TP elasticity).

[Table 6]

Taken together, these results indicate the existence of a strong positive correlation between transaction seasonality and housing heterogeneity.

5 Discussion

5.1 Interpretation and Confounding Effects

We interpret the results of the group comparisons in Section 4.1 and the positive signs and strong statistical significance for the regression coefficients in Section 4.2 as strong evidence for the presence of thick-market effects from matching efficiency in the housing market. Additionally, these results point to an important determinant of the extent of seasonality in a housing market, namely the degree of horizontal heterogeneity of the underlying housing stock.

For our group comparisons, as well as for the fixed-effects model in equation (15), the municipality fixed effect is included to control for fixed local characteristics, which may be correlated with the population of buyers that transact in this geographic segment. For example, variations in annual weather patterns or differences in school holidays between municipalities may lead to different market participation patterns of buyers between these municipalities. These factors could result in some municipalities having more seasonal housing markets than others. If this variation in the transaction patterns of buyers in different municipalities is correlated with the residual price variability of objects in those municipalities, this would create a confounding effect to our results.²⁴ Using only the variation in the extent of seasonality

²⁴In the Supplementary Materials we discuss this possible confounding factor arising from the market-participation decisions of buyers in an alternative framework without thick-market effects.

and price variability *within* municipalities allows us to address this confounding effect.

Thus, the inclusion of municipality fixed effects is an important control with respect to a number of fixed municipality level characteristics. Nevertheless, it may still be the case that buyers differ in terms of market participation patterns across different housing type/size groups. As Section 4.1 showed, these groups differ substantially in terms of both housing heterogeneity and seasonality. On the other hand, buyers in the small apartment markets differ substantially from those in the markets for medium and large houses. The former will consist primarily of small households that may be more flexible in terms of market participation decisions. The latter group will typically consist of households with school-age children, who may only be able to move during school holidays, etc. The estimation with both municipality and group fixed effects addresses this possible endogeneity due to the different temporal behaviour on the demand side of the market.

Finally, the fact that our result holds across several measures of seasonality is also encouraging.

5.2 Robustness

We perform a number of exercises to assess the robustness of our main empirical result. In this section we summarize the outcomes of each of these. A more detailed explanation of our alternative empirical approaches and their results can be found in the Supplementary Materials.

We first assess whether our main finding of an association between seasonality and heterogeneity holds for an alternative measure of seasonality. Specifically, we estimate the variability in the monthly (log) growth of sales volume. The intuition behind such a measure is that a more seasonal market should exhibit greater fluctuations in transactions from one month to the next. We detail the construction of this measure in the Supplementary Materials. Results for this alternative measure are similar to the results for our benchmark measures discussed in Sections 4.1 and 4.2 and can be found in the Supplementary Materials.

Next, rather than using a 5th degree polynomial time trend in the construction of our seasonality measures as discussed in Section 3.2, we use a more flexible time trend specification. In particular, we allow for different (linear) monthly time trends for each year and for different intercepts between years. Our results are robust to such an alternative specification, as well.

Finally, we consider an alternative partitioning by housing type and size. Rather than partitioning each municipality into 6 groups we consider only 4 groups: small apartments (1 bedroom and less), large apartments (2 bedrooms and more), small houses (3 bedrooms and less) and large houses (4 bedrooms and more). The results are again mostly unchanged.

6 Concluding Remarks

There is substantial transaction seasonality in Norwegian housing markets. Moreover, seasonality varies across housing markets. We use cross-sectional variation to provide evidence of thick-market effects from matching efficiency. We construct a simple theoretical framework, which shows a basic implication of thick-market effects - the positive association between horizontal heterogeneity and the extent of seasonality. We then propose an empirical test of this relation. Our empirical results confirm that there is a positive association between horizontal heterogeneity and seasonality in our data set. Therefore, housing heterogeneity is a robust determinant of a housing market's transaction seasonality.

Our theoretical framework is applicable to other markets beyond the housing market. For example, in the labour market, match quality considerations may differ across occupations. Since labour markets are also seasonal, our framework would imply that occupations where match quality is more important also have more seasonal worker flows. Testing this prediction is a promising venue for future research.

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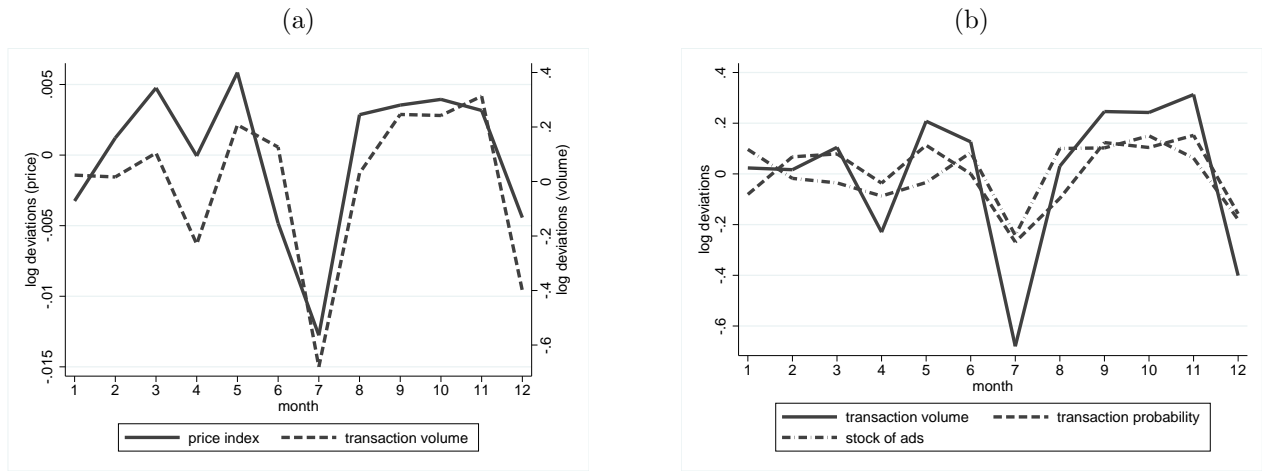
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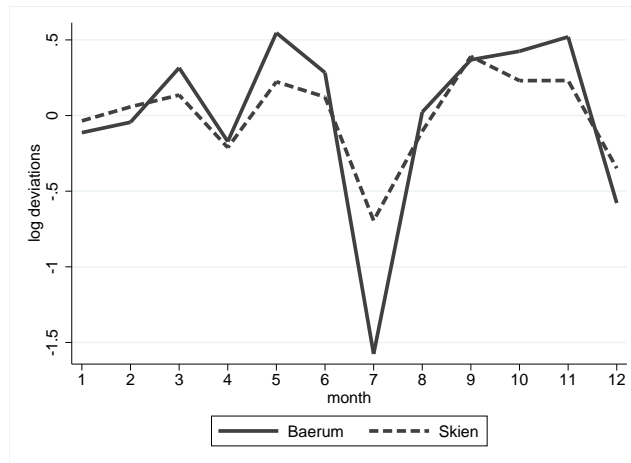
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Figure 1: *Housing Seasonality in Norway, 2011*



Notes. The figures plot the log deviations in a hedonic house price index and total transaction volume (a) and total transaction volume, seller transaction probability, and the stock of ads of houses for sale (b) for all of Norway in 2011 after detrending by a quadratic monthly time trend. The hedonic price index is taken from www.EiendomNorge.no and the stock of ads are from Eiendomsverdi. The total transaction volume and seller transaction probabilities are constructed by the authors.

Figure 2: *Transaction Volume Seasonality for Local Housing Markets. Norway, 2011*



Notes. The figures plot the log deviations in total transaction volume for Skien and Bærum municipalities in 2011 after detrending by a quadratic monthly time trend. The total transaction volume is constructed by the authors.

Table 1: *Summary Statistics*

Variable	Observations	Mean	Std. Dev	Min	Max
<i>Housing Heterogeneity Proxy</i>					
Residual Price Variability	647	0.125	0.032	0.044	0.231
<i>Transaction Volume Seasonality Measure</i>					
TV Beta	647	0.785	0.343	-0.551	1.673
TV Elasticity	647	0.510	0.168	0.048	1.227
<i>Transaction Probability Seasonality Measure</i>					
TP Beta	647	0.774	0.474	-0.727	2.157
TP Elasticity	647	-0.177	0.218	-0.783	0.825
<i>Time-on-market Seasonality Measure</i>					
TOM Beta	647	0.720	0.352	-1.217	1.663

Table 2: *Correlations*

	Price variability	TV Beta	TV Elasticity	TP Beta	TP Elasticity	TOM Beta
Price Variability	1					
TV Beta	0.0906	1				
TV Elasticity	0.1978	0.2021	1			
TP Beta	0.1373	0.6721	0.1158	1		
TP Elasticity	0.0924	0.6372	0.5427	0.4296	1	
TOM Beta	0.0243	0.4118	-0.0279	0.2962	0.2772	1

Table 3: *Group Differences Relative to Small Apartments Group*

Group Difference	Price variability	TV Beta	TV Elasticity	TP Beta	TP Elasticity	TOM Beta
Apartments (medium)	0.00279 (0.00176)	0.110*** (0.0258)	0.0342* (0.0187)	0.237*** (0.0485)	0.0485** (0.0192)	0.0766* (0.0425)
Apartments (large)	0.00933*** (0.00200)	0.0814*** (0.0241)	0.0342* (0.0192)	0.135** (0.0520)	-0.000599 (0.0175)	0.0667 (0.0490)
Houses (small)	0.0349*** (0.00260)	0.0308 (0.0323)	0.0397** (0.0183)	0.0877 (0.0588)	-0.0511** (0.0232)	0.138*** (0.0518)
Houses (medium)	0.0363*** (0.00243)	0.420*** (0.0270)	0.0903*** (0.0196)	0.537*** (0.0476)	0.136*** (0.0261)	0.261*** (0.0450)
Houses (large)	0.0376*** (0.00247)	0.414*** (0.0309)	0.143*** (0.0236)	0.521*** (0.0590)	0.151*** (0.0279)	0.174*** (0.0469)
Observations	647	647	647	647	647	647

Notes. Standard errors are clustered at the municipality level. Each column shows the difference in the average quantity (price variability, TV beta, TV elasticity, etc.) between a group (given in the respective row) and the group of small (≤ 1 bedroom) apartments, after controlling for municipality fixed effects. Price variability is the standard deviation of hedonic regression residuals for properties in a given submarket. TV Beta is the regression coefficient of log transactions in a submarket on log of aggregate transactions minus transactions in the respective municipality. TV Elasticity is the regression coefficient of log transactions in a market on log of stock of houses for sale. TP Beta is the regression coefficient of (log of) transaction probability in a submarket on aggregate transaction probability. TP Elasticity is the regression coefficient of (log of) the transaction probability in a submarket on log of stock of houses for sale. TOM Beta is the regression coefficient of log of the median time-on-market in a submarket on log of the aggregate time-on-market for the corresponding type/size group. Time-on-market is defined as the difference between the property listing and sale dates. A 5th degree polynomial time trend is used in the derivation of each seasonality measure. Individual observations are submarkets with at least 100 total transactions. *** denotes statistical significance at 1%, ** denotes significance at 5%, and * denotes significance at 10%.

Table 4: *Rejections of $H_0 : \gamma_{g_{row}} \geq \gamma_{g_{col}}$ for Groups g_{row} (row) and g_{col} (column)*

Groups	Apartments (medium)	Apartments (large)	Houses (small)	Houses (medium)	Houses (large)
Apartments (small)	TV_β, TP_β	σ_p, TV_β	σ_p	All	All
Apartments (medium)	–	σ_p	σ_p	All	All
Apartments (large)	–	–	σ_p	All	All
Houses (small)	–	–	–	All	All
Houses (medium)	–	–	–	–	$\sigma_p, TV_\beta, TP_\beta,$ TV_ϵ, TP_ϵ

Notes. σ_p = rejection for $\gamma = \text{price variability}$; TV_β = rejection for $\gamma = \text{TV Beta}$; TP_β = rejection for $\gamma = \text{TP Beta}$; 'All' denotes rejection for each of $\gamma = \sigma_p, \gamma = \text{TV Beta}, \gamma = \text{TV Elasticity}, \gamma = \text{TP Beta}, \gamma = \text{TP Elasticity}$, and $\gamma = \text{TOM Beta}$; '–' denotes no test. For each quantity γ there are a total of 15 unique pairwise tests. The test results are obtained using the Bonferroni method for an overall significance level of 5%. Each quantity γ is estimated using a fixed-effects model with municipality fixed effects. Data are clustered at the municipality level. Price variability is the standard deviation of hedonic regression residuals for properties in a given submarket. TV Beta is the regression coefficient of log transactions in a submarket on log of aggregate transactions minus transactions in the respective municipality. TV Elasticity is the regression coefficient of log transactions in a market on log of stock of houses for sale. TP Beta is the regression coefficient of (log of) transaction probability in a submarket on aggregate transaction probability. TP Elasticity is the regression coefficient of (log of) the transaction probability in a market on log of stock of houses for sale. TOM Beta is the regression coefficient of log of the median time-on-market in a submarket on log of the aggregate time-on-market for the corresponding type/size group. Time-on-market is defined as the difference between the property listing and sale dates. A 5th degree polynomial time trend is used in the derivation of each seasonality measure. Individual observations are submarkets with at least 100 total transactions.

Table 5: *Price Variability and Seasonality*

	TV Beta	TV Elasticity	TP Beta	TP Elasticity	TOM Beta
Price variability	5.789*** (0.442)	1.374*** (0.312)	6.391*** (0.819)	2.545*** (0.325)	3.272*** (0.714)
Municipality FE	Yes	Yes	Yes	Yes	Yes
Observations	647	647	647	647	647

Notes. Standard errors are clustered at the municipality level. Price variability is the standard deviation of hedonic regression residuals for properties in a given submarket. TV Beta is the regression coefficient of log transactions in a submarket on log of aggregate transactions minus transactions in the respective municipality. TV Elasticity is the regression coefficient of log transactions in a market on log of stock of houses for sale. TP Beta is the regression coefficient of (log of) transaction probability in a submarket on aggregate transaction probability. TP Elasticity is the regression coefficient of (log of) the transaction probability in a submarket on log of stock of houses for sale. TOM Beta is the regression coefficient of log of the median time-on-market in a submarket on log of the aggregate time-on-market for the corresponding type/size group. Time-on-market is defined as the difference between the property listing and sale dates. A 5th degree polynomial time trend is used in the derivation of each seasonality measure. Individual observations are submarkets with at least 100 total transactions. *** denotes statistical significance at 1%, ** denotes significance at 5%, and * denotes significance at 10%.

Table 6: *Price Variability and Seasonality with Group Fixed Effects*

	TV Beta	TV Elasticity	TP Beta	TP Elasticity	TOM Beta
Price variability	4.032*** (0.703)	0.389 (0.413)	4.291*** (1.084)	3.156*** (0.586)	1.934** (0.961)
Municipality FE	Yes	Yes	Yes	Yes	Yes
Group FE	Yes	Yes	Yes	Yes	Yes
Observations	647	647	647	647	647

Notes. Standard errors are clustered at the municipality level. Price variability is the standard deviation of hedonic regression residuals for properties in a given submarket. TV Beta is the regression coefficient of log transactions in a submarket on log of aggregate transactions minus transactions in the respective municipality. TV Elasticity is the regression coefficient of log transactions in a market on log of stock of houses for sale. TP Beta is the regression coefficient of (log of) transaction probability in a submarket on aggregate transaction probability. TP Elasticity is the regression coefficient of (log of) the transaction probability in a submarket on log of stock of houses for sale. TOM Beta is the regression coefficient of log of the median time-on-market in a submarket on log of the aggregate time-on-market for the corresponding type/size group. Time-on-market is defined as the difference between the property listing and sale dates. A 5th degree polynomial time trend is used in the derivation of each seasonality measure. Individual observations are submarkets with at least 100 total transactions. *** denotes statistical significance at 1%, ** denotes significance at 5%, and * denotes significance at 10%.