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Hot and Cold Seasons in the Housing Market[†]

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Every year housing markets in the United Kingdom and the United States experience systematic above-trend increases in prices and transactions during the spring and summer ("hot season") and below-trend falls during the autumn and winter ("cold season"). House price seasonality poses a challenge to existing housing models. We propose a search-and-matching model with thick-market effects. In thick markets, the quality of matches increases, rising buyers' willingness to pay and sellers' desire to transact. A small, deterministic driver of seasonality can be amplified and revealed as deterministic seasonality in transactions and prices, quantitatively mimicking seasonal fluctuations in UK and US markets. (*JEL* C78, R21, R31)

A rich empirical and theoretical literature has been motivated by dramatic boom-to-bust episodes in regional and national housing markets.[1] Booms are typically defined as times when prices rise and there is intense trading activity, whereas busts are periods when prices and trading activity fall below trend.

While the boom-to-bust episodes motivating the extant work are relatively infrequent and their timing is hard to predict, this paper shows that in several housing markets, booms and busts are just as frequent and predictable as the seasons. Specifically, in most regions of the United Kingdom and the United States, each year a housing boom of considerable magnitude takes place in the second and third quarters of the calendar year (spring and summer, which we call the "hot season"), followed by a bust in the fourth and first quarters (fall and winter, the "cold season").[2] The predictable nature of house price fluctuations (and transactions) is confirmed by real estate agents, who in conversations with the authors observed that during the winter months there is less activity and prices are lower. Perhaps more compelling,

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[1] For example, see Stein (1995), Muellbauer and Murphy (1997), Genesove and Mayer (2001), Krainer (2001), Brunnermeier and Julliard (2008), Burnside, Eichenbaum, and Rebelo (2011), and the contributions cited therein.

[2] Since we use repeat-sale price indexes, changes in prices are not driven by changes in the characteristics of the houses transacted.

publishers of house price indexes go to great lengths to produce seasonally adjusted versions of their indexes, usually the versions that are published in the media. As stated by some publishers:

> *House prices are higher at certain times of the year irrespective of the overall trend. This tends to be in spring and summer... We seasonally adjust our prices because the time of year has some influence. Winter months tend to see weaker price rises and spring/summer see higher increases all other things being equal.*
>
> — Nationwide House Price Index Methodology

> *House prices are seasonal with prices varying during the course of the year irrespective of the underlying trend in price movements. For example, prices tend to be higher in the spring and summer months.*
>
> — Halifax Price Index Methodology

The first contribution of this paper is to systematically document the existence and quantitative importance of these seasonal booms and busts.[3] For the United Kingdom as a whole, we find that the difference in annualized growth rates between hot and cold seasons is 6.5 percent for nominal house prices (5.5 percent for real prices) and 140 percent for the volume of transactions. For the United States as a whole, the corresponding differences are above 4.6 percent for nominal (and real) prices and 146 percent for transactions; US cities tend to display higher seasonality, with differences in growth rates across seasons of 6.7 percent for (real) prices and 152 percent for transactions.[4]

The predictability and size of seasonal fluctuations in house prices pose a challenge to existing models of the housing market. As we argue in the online Appendix, in those models, anticipated changes in prices cannot be large: if prices are expected to be much higher in August than in December, then optimizing buyers will try to shift their purchases to the end of the year, narrowing down the seasonal price differential.[5,6] Our paper tries to answer the question of why presumably informed buyers do not try to buy in the lower-price season and to shed light on the systematic

[3] Studies on housing markets have typically glossed over the issue of seasonality. There are a few exceptions, albeit they have been confined to only one aspect of seasonality (e.g., either quantities or prices) or to a relatively small geographical area. In particular, Goodman (1993) documents pronounced seasonality in *moving patterns* in the United States, Case and Shiller (1989) find seasonality in Chicago house prices and—to a lesser extent—in Dallas. Hosios and Pesando (1991) find seasonality in prices in the City of Toronto; the latter conclude "that individuals who are willing to purchase against the seasonal will, on average, do considerably better."

[4] The data for US cities corresponds to the ten-city Case-Shiller composite. Our focus on these two countries is largely driven by the reliability and quality of the data.

[5] The issue is most evident in frictionless models, where prices reflect the present discounted value of a (presumably long) stream of flow values. Thus, seasonality in rental flows or service costs has to be implausibly large to generate seasonality in house prices. More recent models of the housing market allow for search-and-matching frictions that lead to slightly more complex intertemporal nonarbitrage conditions and a somewhat modified relation between prices and flows. In the online Appendix, we study the canonical models in the literature and argue that these frictions alone cannot account for the high seasonality in the data, calling for an additional mechanism to explain the seasonal patterns.

[6] We note that house price seasonality does not appear to be driven by liquidity related to overall income. Income typically peaks in the last quarter, a period in which house prices and the volume of transactions fall below trend. There is also a seasonal peak in output in the second quarter, and seasonal recessions in the first and third quarters. (See Beaulieu and Miron 1992, and Beaulieu, MacKie-Mason, and Miron 1992.) House price seasonality thus is not in line with income seasonality: prices and transactions are above trend in the second and third quarters.

seasonal pattern. (A lack of scope for seasonal arbitrage does not necessarily imply that most transactions should be carried out in one season nor that movements in prices and transactions should be correlated.) To offer answers to these questions, we develop a model for the housing market that more realistically captures the process of buying and selling houses and can generate seasonal patterns quantitatively comparable to those in the data.

The model builds on two elements of the housing market that help to understand price seasonality. The first element is a search friction. Buyers and sellers potentially face two search frictions: one is locating a house for sale (or a potential buyer), and the other is determining whether the house (once found) is suitable for the buyer (meaning it is a sufficiently good match). The first friction is, in our view, less relevant in the housing market context because advertising by newspapers, real estate agencies, property websites, and so on, can give sufficient information to buyers in order to locate houses that ex ante are in the acceptance set. But houses have many idiosyncratic features that can be valued differently by different buyers: two individuals visiting the same house may attach different values to the property. We model this match-specific quality as a stochastic variable that is fully revealed after the buyer inspects the house. The second model's element is the notion that in a market with more houses for sale, a buyer is more likely to find a better match—what we refer to as "thick-market effect." [7] Specifically, we assume that in a market with more houses, the distribution of match-specific quality first-order stochastically dominates the distribution in a market with fewer houses.

Hence, the model starts from the premise that the utility potential buyers may derive from a house is fully captured by the match-specific quality between the buyer and the house. This match-specific quality is more likely to be higher in a market with more buyers and houses due to the thick-market effect. In a thick market (during the hot season), better matches are more likely to be formed and this increases the probability that a transaction takes place, resulting in a higher volume of transactions. Because better matches are formed, on average, prices will also be higher, provided that sellers have some bargaining power. This mechanism leads to a higher number of transactions and prices in the hot season when there are more buyers and sellers.

In the housing market this pattern is repetitive and systematic. The same half-year is a hot season and the same half-year is a cold season. The higher match-specific quality in the hot season can account for why potential buyers are willing to buy in the hot (high-price) season. But if the amplification mechanism is to explain seasonality, it has to answer two additional questions: one, why are some sellers willing to sell in the cold (low-price) season? In other words, why is there no complete "time agglomeration," whereby markets shut down completely in a cold season? Two, why is the pattern systematic—that is, why do hot and cold markets predictably alternate with the seasons?

To answer these two questions, the paper embeds the above mechanism into a seasonal model of the housing market and studies how a deterministic driver of seasonality can be amplified and revealed as deterministic seasonality in transactions and prices due to the thick-market effects on the match-specific quality. By focusing

[7] The labor literature distinguishes the thick-market effects due to a faster arrival of offers and those due to the quality of the match. Our focus is entirely on the quality effect. See, for example, Diamond (1981), Petrongolo and Pissarides (2006), and Gautier and Teulings (2009).

on a periodic steady state, we are studying a deterministic cycle in which agents are fully aware that they are in a market in which both transactions and prices fluctuate between high and low levels across the two seasons.

Our answer to the first question is related to the presence of search frictions in the form of match-specific quality. In the cold season any seller can decide whether to sell immediately or wait until the hot season, when presumably prospects might be more favorable on average. If a buyer then arrives and a match can be made, the seller has to decide whether to keep searching for a better offer or to sell at the potentially lower price. If he waits until the hot season, he can get, on average, a higher price, provided that he finds a buyer with a good match. There is, however, a probability that he will not find such a buyer to make a transaction; the uncertainty created by this search friction is not present in a standard asset-pricing model, in which agents can always transact at market prices.

Our answer to the second question—why the hot and cold seasons are systematic—is related to our assumption about the desire to move house and the seasonal variations embedded within this decision. We claim that the arrival of the exogenous process by which households want to move (the "propensity to move") has a seasonal component. In the spring and summer months this propensity is higher because, for example, of the school calendar: families with school-age children may prefer to move in the summer, before their children start in new schools. These seasonal differences alone, however, cannot explain the full extent of seasonality we document: in the data, seasonality in houses for sale is much lower than seasonality in the volume of transactions. Moreover, as Goodman (1993) documents, parents of school-age children account for less than one-third of total movers.[8] Most of the explanatory power of the model is due to the thick-market effects on match quality. We show that a slightly higher ex ante probability of moving in a given season (which increases the number of buyers and sellers) can trigger thick-market effects making it appealing to all other existing buyers and sellers to transact in that season. This amplification mechanism can thus create substantial seasonality in the volume of transactions; the extent of seasonality in prices, in turn, increases with the bargaining power of sellers. Intuitively, better matches in the hot season imply higher surpluses to be shared between buyers and sellers; to the extent that sellers have some bargaining power, this leads to higher house prices in the hot season. The calibrated model can quantitatively account for most of the seasonal fluctuations in transactions and prices in the United Kingdom and the United States.

The contribution of the paper can be summarized as follows. First, it systematically documents seasonal booms and busts in housing markets. Second, it develops a search-and-matching model that can quantitatively account for the seasonal patterns of prices and transactions observed in the United Kingdom and the United States. Understanding seasonality in house prices can serve as a first step to understanding how housing markets work and what the main mechanisms governing housing market fluctuations are. As such, it can help to put restrictions on the class of

[8] While weather conditions may make house search more convenient in the summer, it is unlikely that this convenience is worth so much money to the typical house buyer. Indeed, Goodman (1993) finds that seasonal moving patterns are similar across different regions. In addition, as we later report, cities with moderate weather throughout the year, such as Los Angeles and San Diego, also display strong seasonality in prices and transactions.

models needed to characterize housing markets. In other words, seasonality in house prices—what economists and publishers of house price indexes typically ignore or correct for—can contain relevant information to guide the development and selection of appropriate models for housing markets. Our analysis points to the presence of thick-and-thin market externalities; studying their interactions with other frictions at lower frequency might be a fruitful avenue for future research.

The paper is organized as follows. Section I reviews the related theoretical literature and discusses how the thick-and-thin market channel differs from and complements alternative explanations of housing market fluctuations. Section II presents the motivating empirical evidence and Section III introduces the model. Section IV presents the qualitative results and a quantitative analysis of the model; it then discusses additional implications of the model. Section V presents concluding remarks. The online Appendix presents supplementary empirical evidence supporting the model. It then studies the existing canonical models of the housing market and argues that they cannot account for the seasonality observed in the data. Next, it describes the efficiency properties of the model and generalizes the framework to study its robustness to different modelling assumptions; in particular it allows for differential moving costs as alternative triggers of seasonality; it studies different assumptions regarding the observability of the match quality, and different pricing mechanisms (including price posting by sellers). Finally, the online Appendix provides detailed microfoundations for the thick-and thin-market effects. All analytical derivations and proofs are collected in the online Appendix.

I. Related Theoretical Literature

The search-and-matching framework has been applied before to the study of housing markets (for example, see Wheaton 1990, Williams 1995, Krainer 2001, and Albrecht et al. 2007). Recent work on housing market fluctuations, such as Novy-Marx (2009), Diaz and Jerez (2013), and Piazzesi and Schneider (2009), adopt an aggregate matching function (as in Pissarides 2000) and focus on the role of market tightness (the ratio of the number of buyers to the number of sellers) in determining the probability of transactions taking place. These papers study the amplified response of housing markets to an unexpected shock. We instead focus on predictable cycles, with both sellers and buyers being fully aware of being in such periodic cycle. We distinguish the probability of making a contact and the probability that the house turns out to be a good match. The contact probability is always one in our model, but the match quality drawn is a random variable. In this sense, our setup is closest to Jovanovic (1979), which also emphasizes the stochastic nature of the match-specific quality for the labor market, and Krainer (2001) for the housing market. In contrast to previous models which focus on market tightness, transactions and prices in our set-up are governed by the distribution of match-specific quality.

Our paper complements the seminal work by Krainer (2001) and Novy-Marx (2009) by highlighting a new mechanism that can account for some of the regularities observed in housing markets. Both Krainer (2001) and Novy-Marx (2009) also refer to "hot and cold" markets; however, in both studies the nature as well as the meaning of hot and cold markets is different than in our paper. The key idea in Novy-Marx (2009) is that, if for any reason the ratio of buyers to sellers (tightness)

unexpectedly increases, houses can sell more quickly, decreasing the stock of sellers in the market. This in turn increases the relative number of buyers to sellers even more, amplifying the initial shock. As a result, the outside option of sellers improves, leading to higher prices. Thus, the entire amplification effect operates through market tightness. In our model, instead, market tightness plays no role; indeed, it is constant across all seasons. If an agent receives a shock that forces her to move, she becomes a potential buyer and a potential seller simultaneously and overall tightness does not change. The amplification mechanism in our model comes instead from the quality of the matches. In the hot season there are both more buyers and more sellers; the availability of a bigger stock of houses for sale improves the overall efficiency of the market, as buyers are more likely to find a better match. Put differently, our explanation relies on market thickness (the number of buyers and sellers) and its effect on the quality of matches, whereas Novy-Marx's hinges on tightness. This difference leads to crucially different predictions for the correlation between prices and transactions. In Novy-Marx (2009), the number of house transactions is not necessarily higher when prices are high; that is, his model does not generate a positive correlation between prices and the volume of transactions, which is one of the salient features of housing markets (Stein 1995). Specifically, in Novy-Marx (2009), a large increase in the number of sellers and buyers that does not alter tightness would not alter prices at all, even if it substantially increases the volume of transactions; similarly, a decline in the number of sellers in his model leads to an increase in tightness, lower volume of transactions, and higher prices, thus generating a negative comovement between prices and transactions. Instead, our model generates a positive correlation between prices and transactions, consistent with the data. As Wheaton (1990) has pointed out, moving houses most of the time means both selling a house and buying another one and hence, in this context, a model in which tightness plays a subdued role is appealing. In our model, a hot market is one with high prices, more buyers and sellers, and an unambiguously larger number of transactions.[9] Of course, in practice tightness and thickness of the market can operate simultaneously, and their role might vary at different frequencies. In this sense, our paper complements the existing literature focusing on tightness.

In our paper, "hot-and-cold markets" also are different from those in Krainer (2001), who studies the response of housing markets to an aggregate shock that affects the fundamental value of houses—his model cannot generate quantitatively meaningful fluctuations in prices unless the aggregate shock is very persistent. A deterministic cycle in Krainer's model is equivalent to setting the persistence parameter to zero, in which case his model predicts virtually no fluctuation in prices. Our setup is different from Krainer (2001) in that it brings in thick-market effects

[9] As in Novy-Marx (2009), our model has predictions for average time on the market (TOM). Specifically, the model predicts that a house put up for sale in the cold season will take longer to sell. There is a difference, however, between our mechanism and that in models emphasizing tightness. Our model predicts higher probability of a transaction and shorter average TOM for both buyers and sellers in the hot season. (We emphasize that the prediction is about the correlation between average time on the market and prices *over time*, not across sellers—or buyers—within a time period. See, for example, Krainer 2001, and Diaz and Jerez 2013.) Models that focus on market tightness predict an inverse relation between buyer's and seller's TOM (average TOM is short for buyers but long for sellers when tightness is high). Instead, our model predicts they move in the same direction. Empirical studies focus on sellers' TOM, largely because data on buyers' TOM is less easily observed. This prediction could potentially be tested empirically, as more data on the buyer's side are gathered.

which, due to their amplification, are able to generate quantitatively large fluctuations in transactions and prices.[10] In the online Appendix we expand on this point and argue that in the absence of a thick-market effect, existing models of the housing market are unable to account for the seasonality in the data.

Finally, we follow the literature (for example, see Wheaton 1990 and Krainer 2001) by assuming exogenous moving shocks. This essentially abstracts from the decision to dissolve a match, which would potentially require a role for school enrollments, marriages, job changes, and other socioeconomic determinants outside our model. The main potential contribution of allowing endogenous moving decision is to account for the seasonality in vacancies (homes for sale). Since we do not have data that is more fundamental (e.g., seasonality in shocks that change the match quality) than the observed seasonality in vacancies, we do not attempt to predict the seasonality in vacancies. Instead, in the calibration, we choose to match the seasonality in vacancies observed in the data, and study its effects on prices and transactions; thus the potential amplification mechanism through the endogenous moving decision is already embedded in the seasonality in vacancy.

II. Hot and Cold Seasons in the Data

In this section we study seasonality in housing markets in the United Kingdom and the United States at different levels of aggregation. The focus on these two countries is due to the availability of constant-quality house price series.[11] As already noted, publishers of house price indexes produce both seasonally adjusted (SA) and nonseasonally adjusted (NSA) series. This is also the case for transactions. In our analysis, we use exclusively the (raw) NSA series to compute the extent of seasonality.[12] In what follows, we first describe the data sources and assess the degree of seasonality in the data. Next, we discuss the behavior of other variables related to the housing market. Finally, we provide empirical evidence motivating the mechanism we propose.

A. *Data*

United Kingdom.—As a source for house price data, we use the repeat-price index based on Case and Shiller's (1987) method, produced by the Land Registry for England and Wales. The repeat-sale index measures average price changes in repeat sales of the same properties; as such, the index is designed to control for the characteristics of the homes sold.[13] The index is constructed at different levels of geographic aggregation and starts in 1995:1. In the interest of space, we discuss here the results for the main planning regions and in the online Appendix we report the

[10] Unlike Krainer (2001), we also model the endogenous evolution of the number of vacancies and buyers over time.

[11] Constant-quality indexes mitigate concerns with compositional changes in the types of houses transacted across seasons. Results for other countries show qualitatively similar seasonal patterns, but we are less confident about the comparability of the data.

[12] In the online Appendix we show the implied seasonal patterns based on the publishers' in-house adjustments.

[13] The approach significantly limits the extent to which changes in the composition of the sample of houses transacted can influence the price index. Specifically, using information on the values of the same physical units at two points in time controls for differences in housing attributes across properties in the sample.

results at finer levels of disaggregation.[14] To compute real price indexes, we later deflate the house price indexes using the NSA retail price index (RPI) provided by the UK Office for National Statistics.

For transactions, we use the data on sales volumes also published by the Land Registry.

United States.—We use two sources for house prices in the United States. The first is the Federal Housing Finance Agency (FHFA), which took over the Office of Federal Housing Enterprise Oversight; we focus on the repeat-sale purchase-only index, which starts in 1991:I. The second source is Standard and Poor's (S&P) Case-Shiller price series for major US cities, which starts in 1987:I. To compute real price indexes, we use the NSA consumer price index (CPI) provided by the US Bureau of Labor Statistics.[15]

Data on the number of transactions at the regional level come from the National Association of Realtors (NAR), and correspond to the number of sales of existing single-family homes. Data for US cities come from S&P and correspond to sales pair counts on which the repeat-price index is based.

B. *Extent of Seasonality*

We focus our study on deterministic seasonality, which is easier to understand (and to predict) for buyers and sellers (unlikely to be all econometricians), and hence most puzzling from a theoretical point of view. In the United Kingdom and the United States, prices and transactions in both the second and third quarters are above trend, while in both first and fourth quarters they are below trend. For ease of exposition, we group data into two broadly defined seasons—second and third quarter, or "hot season," and fourth and first quarter, or "cold season." (We use interchangeably the terms "hot season" and "summer" to refer to the second and third quarters, and "cold season" and "winter" to refer to the first and fourth quarters.)

In the next set of figures, we depict in dark (red) bars the average (annualized) price increase from winter to summer, $\ln\left(\frac{P_S}{P_W}\right)^2$, where P_S is the price index at the end of the hot season and P_W is the price at the end of the cold season. Correspondingly, we depict in light (blue) bars the average (annualized) price increase from summer to winter, $\ln\left(\frac{P_{W'}}{P_S}\right)^2$, where $P_{W'}$ is the price index at the end of the cold season in the following year. We plot similar figures for transactions.

[14] There are two other sources providing quality-adjusted NSA house price indexes: one is the Department of Communities and Local Government and the other is Halifax, one of the country's largest mortgage lenders. Both sources report regional price indexes based on hedonic regressions. The results are consistent across all sources (see the online Appendix.) Other house price publishers, such as the Nationwide Building Society (NBS), report quality adjusted data but they are already SA (the NSA data are not publicly available). The NBS, however, reports in its methodology description that June is generally the strongest month for house prices and January is the weakest; this justifies the seasonal adjustment they perform in the published series. In a somewhat puzzling paper, Rosenthal (2006) argues that seasonality in the NBS data is elusive; we could not, however, gain access to the NSA data to assess which of the two conflicting assessments (the NBS's or Rosenthal's) was correct. We should perhaps also mention that Rosenthal (2006) also reaches very different conclusions from Muellbauer and Murphy (1997) with regards to lower-frequency movements.

[15] There is little seasonality in the US CPI, a finding first documented by Barsky and Miron (1989), and hence the seasonal patterns in nominal and real housing prices coincide.

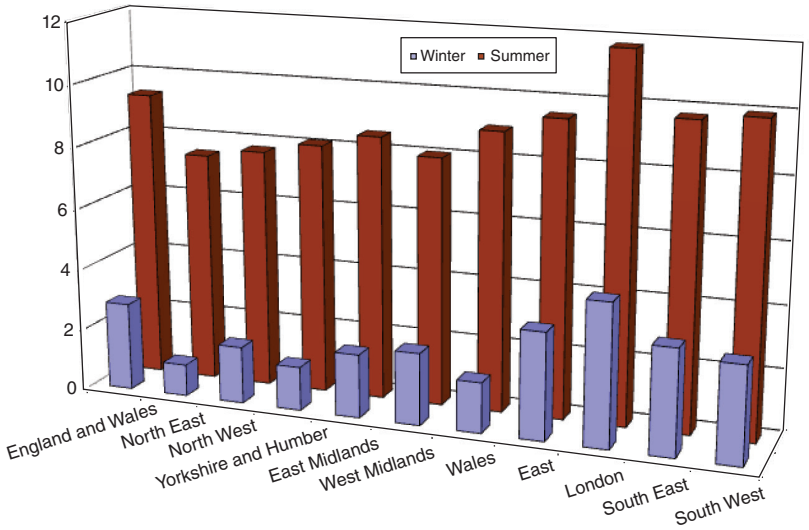

Figure 1. Average Annualized Percentage House Price Changes in Summer and Winter, by Region

Note: Annualized percentage growth rates of house prices in summers (second and third quarters) and winters (fourth and first quarters) in the UK and its regions.

Source: Land Registry (1996–2012)

The extent of seasonality for each geographical unit can then be measured as the difference between the two bars. This measure nets out lower frequency fluctuations affecting both seasons. In the model we later present, we use a similar metric to gauge the extent of seasonality.

Housing Market Seasonality in the United Kingdom

Nominal and Real House Prices.—Figure 1 reports the average annualized percent price increases in the summer and winter from 1996 through to 2012 using the regional price indexes provided by the Land Registry. During the period analyzed, the average nominal price increases in the winter were around 3 percent in all regions except for London. In the summer, the average growth rates were above 8 percent in all regions, except for the North East and North West. As shown in the graph, the differences in growth rates across the two broad seasons are generally very large and economically significant, with an average of 6.5 percent for all regions. Similar seasonal patterns emerge with other sources of constant-quality prices going back to 1983.[16] While the average growth rates differ across different time periods, the seasonal pattern appears extremely robust.

The seasonal pattern of real house prices (that is, house prices relative to the NSA aggregate price index) depends also on the seasonality of aggregate inflation. In the United Kingdom, overall price inflation during this period displayed a small degree of seasonality. The difference in overall inflation rates across the two seasons, however,

[16] See also Figure A1 in the online Appendix for results based on alternative sources.

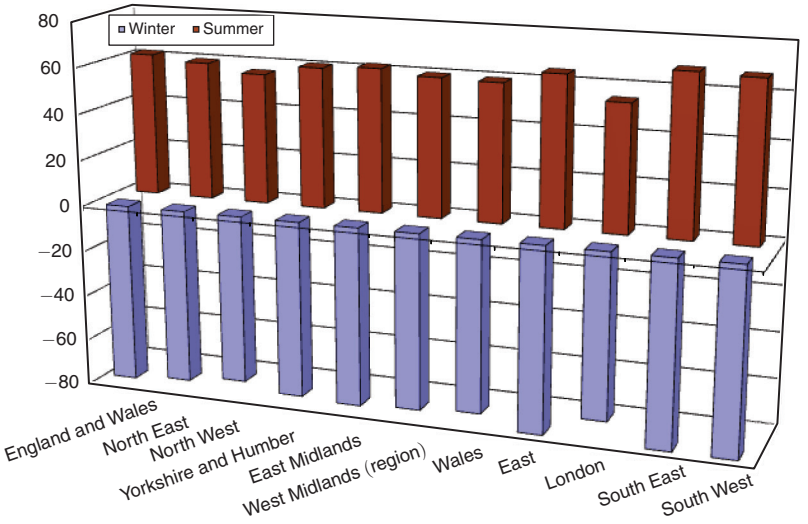

Figure 2. Average Annualized Percentage Changes in Transactions in Summer and Winter, by Region

Note: Annualized percentage growth rates of the number of transactions in summers (second and third quarters) and winters (fourth and first quarters) in the UK and its regions.

Source: Land Registry (1996–2012)

can hardly "undo" the differences in nominal house price inflation, implying a significant degree of seasonality also in real house prices (see Figure A2 in the online Appendix). Netting out the effect of overall inflation reduces the differences in growth rates between winters and summers to a countrywide average of 5.5 percent.[17]

Number of Transactions.—Seasonal fluctuations in house prices are accompanied by qualitatively similar fluctuations in the number of transactions, as illustrated in Figure 2.[18] As the figure shows, the number of transactions increases sharply in the summer term and accordingly declines in the winter term. The average difference in growth rates during this period, our metric for seasonality, was 139 percent.

Statistical Significance of the Differences between Summer and Winter.—We test the statistical significance of the differences in growth rates across seasons, $\left[\ln\left(\frac{P_S}{P_W}\right)^2 - \ln\left(\frac{P_{W'}}{P_S}\right)^2\right]$, using a t-test on the equality of means.[19] Table 1 reports the

[17] We also looked at more disaggregated data, using the Halifax series, distinguishing between first-time buyers and former-owner occupiers, as well as purchases of newly built houses versus existing houses. Seasonal patterns are qualitatively similar across the various groups, but tend to be quantitatively stronger for former-owner occupiers and existing houses. The results are reported in Table A1 in the online Appendix.

Our model, by abstracting from construction, will speak more directly to the evidence on existing houses, and, as it will become clear, former-owner occupiers.

[18] A different dataset from the Council of Mortgage Lenders going back to 1983 (and to 1974 for some regions) show similar seasonal patterns. See Figure A3 in the online Appendix.

[19] The test on the equality of means is equivalent to the t-test on the slope coefficient from a regression of annualized growth rates on a dummy variable that takes value 1 if the observation falls on the second and third quarter and 0 otherwise. The dummy coefficient captures the annualized difference across the two seasons, regardless of the frequency of the data (provided growth rates are annualized). To see this, note that the annualized growth rate in, say, the hot season, $\ln\left(\frac{P_S}{P_W}\right)^2$, is equal to the average of annualized quarterly growth rates in the summer term

Table 1—Difference in Annualized Percentage Changes in UK House Prices and Transactions between Summer and Winter, by Region, 1996–2012

	Nominal house price		Real house price		Volume of sales	
Region	Difference	SE	Difference	SE	Difference	SE
England and Wales	6.5***	(2.3)	5.5**	(2.5)	139.2***	(15.6)
North East	6.4**	(2.9)	5.5*	(3.1)	135.0***	(17.6)
North West	5.9**	(2.5)	5.0*	(2.7)	129.0***	(15.9)
Yorks and Humber	6.7**	(2.6)	5.8**	(2.8)	136.8***	(16.6)
East Midlands	6.5**	(2.5)	5.5**	(2.7)	139.1***	(16.6)
West Midlands	5.7**	(2.3)	4.8*	(2.5)	135.5***	(15.7)
Wales	7.3***	(2.6)	6.4**	(2.8)	133.3***	(16.6)
East	6.1**	(2.4)	5.1*	(2.6)	144.8***	(16.1)
London	7.1***	(2.5)	6.2**	(2.6)	125.0***	(15.0)
South East	6.3**	(2.4)	5.4**	(2.6)	152.8***	(15.7)
South West	6.8***	(2.5)	5.9**	(2.7)	150.3***	(16.8)

Note: The table shows the average annualized percentage differences (and standard errors), by region for 1996–2012.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Source: Land Registry Repeat Sale Index

average differences in growth rates across seasons and standard errors, together with the statistical significance. The first two columns show the results for seasonality in nominal house prices; the third and fourth columns show the corresponding results for real house prices and the last two columns show the results for the volume of sales.[20] The differences in price changes across seasons are quite sizable for most regions, in the order of 6 to 7 percent on average in nominal terms and 5 to 6 percent on average in real terms; from a statistical point of view, the results are significant at the 10 percent level (or lower). For transactions, the differences reach 139 percent for the country as a whole, and are statistically significant at the 1 percent level. Taken together, the data point to a strong seasonal cycle in all regions, with a large increase in transactions and prices during the summer relative to the winter.

Housing Market Seasonality in the United States

Nominal and Real House Prices.—Figure 3 illustrates the annualized nominal house price increases for different regions from FHFA and Figure 4 shows the plot using the S&P's Case-Shiller indexes for major cities. As shown, for most US regions the seasonal pattern is qualitatively similar to that in the United Kingdom, albeit the extent of seasonality is somewhat smaller averaging 4.6 percent for nominal prices and 4.8 percent for real prices. For some of the major US cities, however, the degree of seasonality is comparable to (and even higher than) that in the United Kingdom, as illustrated in Figure 4.

$\ln\left(\frac{P_S}{P_W}\right)^2 = 2\ln\left(\frac{P_3}{P_1}\right) = \frac{1}{2}\left[4\ln\left(\frac{P_3}{P_2}\right) + 4\ln\left(\frac{P_3}{P_2}\right)\right]$, where the subindices indicate the quarter, and, correspondingly, $2\ln\left(\frac{P_{1'}}{P_3}\right) = \frac{1}{2}\left[4\ln\left(\frac{P_{1'}}{P_4}\right) + 4\ln\left(\frac{P_4}{P_3}\right)\right]$. Hence a regression with quarterly (or semester) data on a summer dummy will produce an unbiased estimate of the average difference in growth rates across seasons. We use quarterly data to exploit all the information and gain on degrees of freedom.

[20] Tables A2a and A2b in the online Appendix show the results at geographically more disaggregated levels and Table A3 shows the corresponding information at the regional level using alternative datasets.

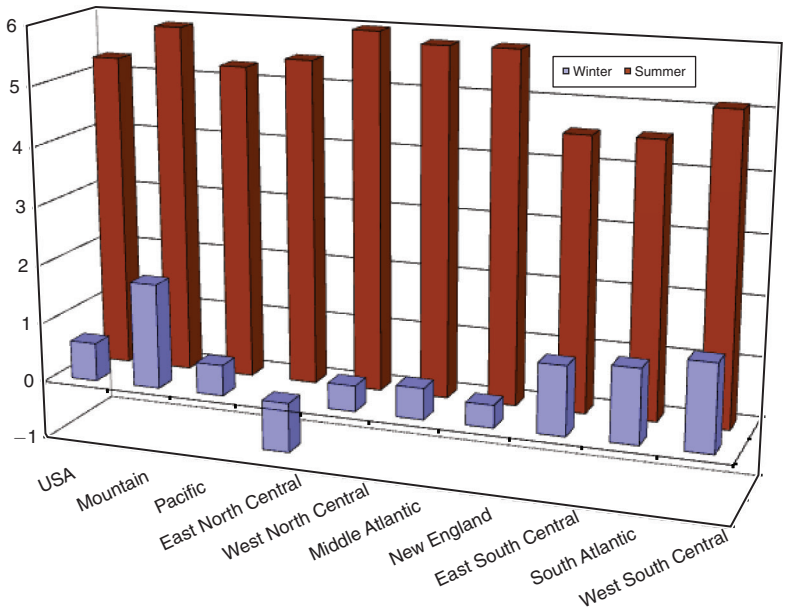

Figure 3. Average Annualized US House Price Increases in Summer and Winter by Region

Note: Annualized percentage price growth rates in summers (second and third quarters) and winters (fourth and first quarters) in the United States and its regions.

Source: FHFA (1991–2012)

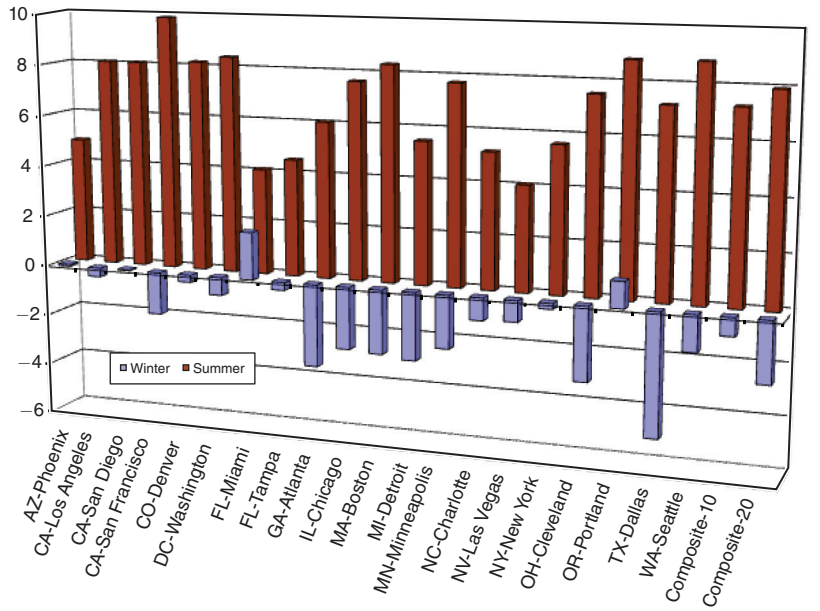

Figure 4. Average Annualized US Percentage House Price Changes in Summer and Winter, by US City

Notes: Annualized percentage price growth rates in summers (second and third quarters) and winters (fourth and first quarters) by US city. (For some cities, the index starts later.)

Source: S&P Case and Shiller (1987–2012)

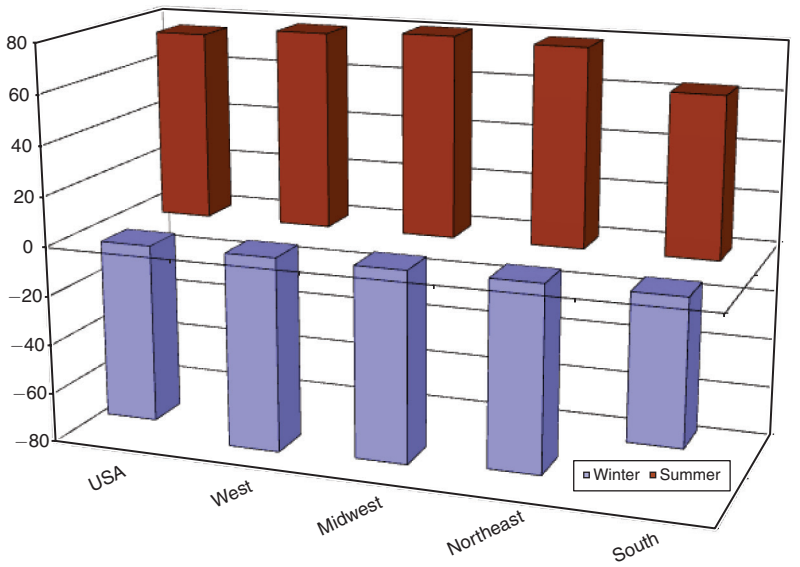

FIGURE 5. US AVERAGE ANNUALIZED PERCENTAGE INCREASES IN TRANSACTIONS IN SUMMER AND WINTER, BY REGION

Note: Annualized percentage growth rates of the number of transactions in summers (second and third quarters) and winters (fourth and first quarters) in the United States and its regions.

Source: NAR (1991–2012)

Transactions.—Figure 5 shows the annualized growth rates in the number of transactions from 1991 to 2012 for main census regions; the data come from the National Association of Realtors (NAR).[21] As was the case for the United Kingdom, the seasonality of US transactions is overwhelming: the volume of sales rises sharply in the summer and falls in the winter.

Statistical Significance of the Differences between Summer and Winter.—We summarize the differences in growth rates across seasons and report the results from a test on mean differences in Tables 2 and 3. Table 2 shows the results for prices using FHFA's Census-division levels and for transactions using NAR's Census-level data. Table 3 shows the results using S&P's Case-Shiller city-level data on prices and transactions.

For the United States as a whole, the differences in annualized growth rates in nominal prices are in the order of 4.6 percent (4.8 percent for real prices) and statistically significant at standard levels. There is some variation across regions, with some displaying low seasonality (South) and others (Midwest and Northeast) displaying significant levels of seasonality. Interestingly, the Case-Shiller index for US cities displays even higher levels of seasonality, comparable to and even higher than the levels observed in UK regions, with some variation across cities. The ten-city composite index shows a statistically significant seasonality of 7.2 percent for nominal prices and 6.7 percent for real prices.

[21] The series actually starts in 1989, but we use 1991 for comparability with the FHFA-census-level division price series; adding these two years does not change the results.

Table 2—Difference in Annualized Percentage Changes in US House Prices and Transactions between Summer and Winter, by Region, 1991–2012

			Nominal house price		Real house price		Volume of sales	
	Region	Division	Difference	SE	Difference	SE	Difference	SE
1	USA	USA	4.6***	(1.5)	4.8***	(0.3)	146.5***	(13.7)
2	West	Mountain	4.1*	(2.3)	4.4***	(0.3)	120.5***	(15.9)
2		Pacific	4.7	(3.1)	5.0***	(0.3)		
3	Midwest	East North Central	6.3***	(1.3)	6.5***	(0.6)	156.6***	(15.7)
3		West North Central	5.5***	(1.1)	5.6***	(0.4)		
4	Northeast	Middle Atlantic	5.3***	(1.6)	5.5***	(0.2)	156.5***	(11.2)
4		New England	5.4***	(1.9)	5.8***	(0.3)		
5	South	East South Central	3.4***	(1.1)	3.7***	(0.5)	152.7***	(13.0)
5		South Atlantic	3.3*	(1.9)	3.4***	(0.3)		
5		West South Central	3.6***	(0.8)	3.7***	(0.2)		

Note: The table shows the percentage average differences (and standard errors), by region for 1991:I–2012:I.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Sources: For prices, FHFA Purchase Only Repeat Sale Index. For volume, NAR Existing single family homes series.

Table 3—Difference in Annualized Percentage Changes in US House Prices and Transactions between Summer and Winter, by City, 1987–2012

	Nominal house price		Real house price		Volume of sales	
City	Difference	SE	Difference	SE	Difference	SE
AZ-Phoenix	4.8	(3.2)	3.6	(3.2)	111.6***	(10.2)
CA-Los Angeles	8.4***	(2.8)	7.2**	(2.8)	113.9***	(10.8)
CA-San Diego	8.0***	(2.6)	6.8***	(2.6)	120.4***	(13.3)
CA-San Francisco	11.5***	(2.9)	10.3***	(2.9)	147.1***	(10.9)
CO-Denver	8.4***	(1.3)	7.2***	(1.3)	189.2***	(8.8)
DC-Washington	9.1***	(2.0)	7.9***	(2.0)	187.1***	(7.4)
FL-Miami	2.2	(2.6)	1.0	(2.6)	116.3***	(7.2)
FL-Tampa	4.8**	(2.2)	3.6	(2.2)	119.3***	(8.1)
GA-Atlanta	9.2***	(2.1)	7.9***	(2.0)	155.7***	(10.0)
IL-Chicago	10.0***	(1.9)	8.8***	(1.9)	216.9***	(12.0)
MA-Boston	10.8***	(1.5)	9.6***	(1.6)	237.1***	(6.8)
MI-Detroit	8.1***	(2.5)	6.8**	(2.6)	165.0***	(24.8)
MN-Minneapolis	9.8***	(2.4)	8.5***	(2.4)	100.9***	(19.4)
NC-Charlotte	6.1***	(1.0)	4.9***	(0.9)	183.5***	(11.4)
NV-Las Vegas	4.9	(3.1)	3.7	(3.1)	109.4***	(15.1)
NY-New York	5.8***	(1.6)	4.6***	(1.8)	163.0***	(10.2)
OH-Cleveland	10.4***	(1.2)	9.1***	(1.2)	235.9***	(10.8)
OR-Portland	7.8***	(1.7)	6.6***	(1.6)	174.0***	(11.0)
TX-Dallas	11.9***	(1.6)	9.7***	(1.5)	173.8***	(19.3)
WA-Seattle	10.2***	(1.9)	8.9***	(1.9)	161.6***	(11.5)
Composite-10	8.0***	(1.9)	6.7***	(2.0)	152.6***	(6.5)
Composite-20	10.3***	(3.3)	8.0**	(3.3)	154.2***	(7.8)

Note: The table shows the average percentage differences (and standard errors), by region for 1987–2012.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Sources: S&P Case-Shiller Price Index and Sales pair counts. Some of the series start after 1987.

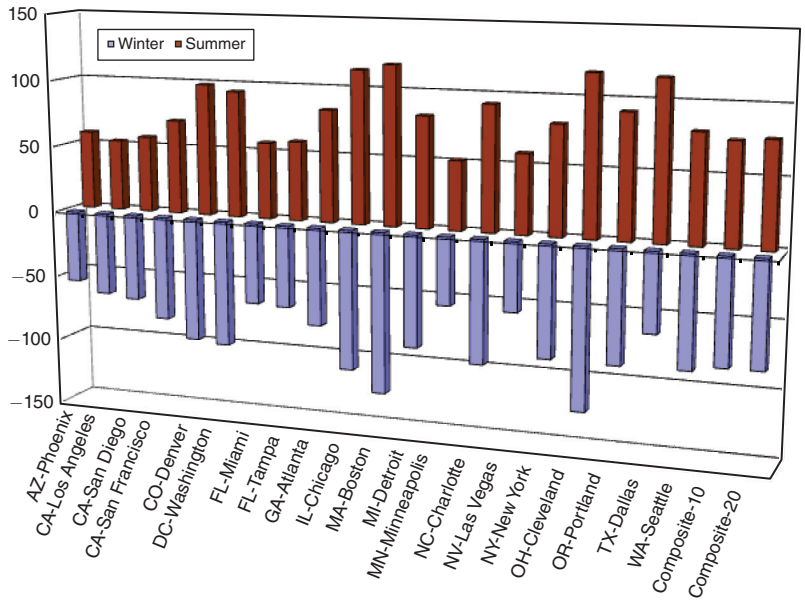

Figure 6. US Average Annualized Percentage Changes in Transactions in Summer and Winter, by City

Notes: Annualized percentage growth rates of the volume of transactions in summers (second and third quarters) and winters (fourth and first quarters) by US city. (For some cities, the index starts later.)

Source: S&P Case and Shiller (1987–2012)

The seasonality in the volume of transactions is comparable to (or higher than) that in the United Kingdom, with an average difference in growth rates across seasons of 146 percent for the United States as a whole and of 152.6 percent for the ten-city composite.

C. *Other Housing Variables and Cross-Market Comparisons*

As part of our study of house markets, we also analyzed data on rental prices, but we were unable to identify a seasonal pattern in either country.[22] This is in line with anecdotal evidence suggesting that rents are sticky. Similarly, interest rates did not exhibit a seasonal pattern in the last four decades of data.[23] In the interest of space,

[22] We studied the average registered private rents collected by UK Housing and Construction Statistics. We run regressions using as dependent variables both the rent levels and the log of rents on a dummy variable taking a value of 1 in the second and third quarters and 0 otherwise, detrending the data in different ways. We found no evidence of deterministic seasonality. For the United States, the Bureau of Labor Statistics (BLS) provides two series that can serve as proxies: one is the NSA series of owner's equivalent rent and the second is the NSA rent of primary residence; both series are produced for the construction of the CPI and correspond to averages over all US cities. For each series, we run similar regressions as for the UK. The results yielded no discernible pattern of seasonality. We take this as only suggestive as, of course, the data are not as clean and detailed as we would wish.

[23] We investigated seasonality in different interest rate series published by the Bank of England: the repo (base) rate, an average interest rate charged by the four major UK banks before the crisis (Barclays Bank, Lloyds Bank, HSBC, and National Westminster Bank), and a weighted average standard variable mortgage rate from banks and Building Societies. None of the interest rate series displays seasonality. For the United States, we studied data on mortgage rates produced by the Board of Governors of the Federal Reserve System, corresponding to contract interest rates on commitments for fixed-rate first mortgages; the data are quarterly averages beginning in 1972 and

we do not report the results in the paper. In the model we present later, we will work under the assumption that rents and interest rates are aseasonal.

The data description makes it evident that seasonal cycles are present across most of the United Kingdom and the United States, although with some heterogeneity with regards to intensity. In particular, though most US cities display strong seasonality, cities such as Miami and Las Vegas show little (or statistically insignificant) variation over the season. Given the data limitations (20 observations on price seasonality corresponding to the cities in the Case-Shiller data), it would be virtually impossible to draw causal links on the potential triggers of seasonality: e.g., winters are mild in these cities but also there is a larger population of elderly people, factors which are intimately related. We note, though, that the mildness of a winter per se does not straightforwardly predict aseasonality, as cities such as Los Angeles, San Diego, or San Francisco display strong seasonality in prices, despite their benign weather.[24] A perhaps more likely trigger of seasonality is the school calendar.[25] As noted earlier, however, only a small portion of the population of potential home buyers have school-age children.[26] One of the model's implications is that even slight differences in the "fundamentals" of the seasons have the potential to trigger thick-market effects with large swings in the volume of transactions and prices. Hence, in equilibrium, most people end up transacting in the summer. This is consistent with the data, illustrated in Figure A4 in the online Appendix, which shows that people in different life-cycle stages (not just parents of school-age children) tend to move in the summer—a regularity originally noted by Goodman (1993).

We also note that US cities tend to display more seasonality than the United States as a whole, a pattern that can be rationalized by our model. Concretely, the model predicts that there should be more price seasonality in markets in which sellers have higher bargaining power. The assumption needed to explain the urban-rural variation is that sellers have more bargaining power in urban areas, where population density and supply restrictions are likely more important.

the original data are collected by Freddie Mac. Consistent with the findings of Barsky and Miron (1989) and the evidence from the United Kingdom, we did not find any significant deterministic seasonality.

[24] In their study of stock market seasonality, Kamstra, Kramer, and Levi (2003) argue that due to a seasonal affective disorder (SAD), people tend to take less risk in the fall and winter, driving up stock returns in these seasons. The incidence of SAD in the American population, however, is very low (around 5 percent) and provided it affects both potential buyers and homeowners equally, its general equilibrium effects are far from obvious. In particular, if houses are perceived as safe assets, the demand for houses will decrease and the supply will increase in the summer, as people seek to take more risk—and buy risky assets. In this case, prices will be lower in the summer. Conversely, if houses are considered risky assets, the demand for houses will increase and the supply will decrease in the summer. This would generate an increase in prices, but not necessarily an increase in the volume of transactions in the summer. Given its low incidence and its ambiguous effects on price and transaction seasonality, we believe SAD alone would not be able to generate the large response in transactions and prices. An amplification effect as the one proposed in our model would still be needed to account for the patterns in the data.

[25] There is a positive correlation between seasonality and the ratio of school-age children to elderly people in a city. However, the results seem entirely driven by Miami and Tampa. A possible mitigating factor of the school calendar is the presence of investors and second-home buyers, who are likely less constrained by the school calendar. The four US cities with relatively low price seasonality fall in states with high participation of vacation houses. The correlation between price seasonality and the share of "vacation" houses in the state, using US Census data is -0.6 (meaning price seasonality is lower if the city is in a state with a high share of vacation houses). We acknowledge this is based on very few observations and only captures one motive for holding a second-home (vacation); hence, we would not like to overemphasize this result. The lack of power soon becomes a problem and we cannot at this stage pinpoint the exact seasonal trigger.

[26] The fraction of movers with children between 6 and 17 years old is 0.22 according to the American Housing Survey 1999.

A cross-city study of the extent of seasonality is beyond the scope of our paper, as the limited number of city observations precludes a proper multivariate regression analysis; but we note here that, consistent with our model's predictions, price seasonality is positively correlated with the price-to-rent ratio (which, in turn increases with the degree of bargaining power in our model).[27]

Some may argue that cities by their sheer size, are likely to be "thicker" throughout the year and hence seasonal differences in thickness are relatively unimportant. Anecdotal evidence, however, suggests that even within cities, housing markets can be highly segmented, as people tend to search in relatively narrow neighborhoods and geographic areas (e.g., to be close to schools, jobs, families). Thus, for example, London or Chicago as a whole are not the relevant sizes of the local housing market, and it would be improper to use these cities as boundaries to define market thickness (e.g., for those familiar with London's geography and social structure, people searching in South Kensington will never search in the East End). In other words, seemingly large cities may mask a collection of relatively smaller and segmented housing markets that can see significant changes in thickness throughout the year. A limitation of the data is hence that we cannot meaningfully compare thickness across geographic units.

Finally, we note that seasonality appears to be slightly higher in the post-2007 period, although it is too early to draw general conclusions about a cyclical link. As we gather more data (and cycles) over time, we may be able to discern whether seasonality indeed increases in recessions.[28]

D. *Match Quality and Seasons in the Data*

The key idea at the core of the model we propose is that, due to the thick-market effect, the average quality of matches formed in the summer is higher than in the winter. We use individual household data from the American Housing Survey (AHS) to check the empirical plausibility of this idea. Though the quality of the match is house-owner specific and not directly observable to the econometrician, we consider three proxies that should be correlated with it.

The first proxy is the duration of the match. The premise is that, in practice, if the house is a good fit for the household, the household will tend to stay longer; in other words, the duration of stay should be indicative of the quality of the match. (In the labor literature the duration of the employment relationship is often used as a proxy for the quality of the match.) We hence ask whether in the data, matches formed in the hot season tend to last longer.

The analysis uses data on households for which we observe a full duration spell—that is, households who report the date of the last move and the date of the move previous to that. (Duration is measured as the difference in years between the last

[27] The correlation between price seasonality and the price-to-rent ratio in the data is about 0.3. Data on price-to-rent ratios come from the 2009 *New York Times* index. Similarly, price seasonality in US cities appears to be positively correlated with the Wharton index of supply restrictions (supply restrictions should confer sellers higher bargaining power); however, as noted earlier, these correlations are based on the very small sample of cities available in our study and hence should be read with caution.

[28] This would be consistent with our model: during cyclical busts, the incentives to transact during the summer (the thick market) are even stronger, as the chances to find a better match are relatively higher.

Table 4—Duration of the Match and Season in which Match was Formed

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Moved into unit in the Summer	0.03* [0.02]	0.04** [0.02]	0.05** [0.02]	0.05** [0.02]	0.05*** [0.02]	0.05*** [0.02]	0.05*** [0.02]
(log) family income		0.10*** [0.01]	0.09*** [0.01]	0.10*** [0.01]	0.09*** [0.01]	0.09*** [0.01]	0.09*** [0.01]
Number of persons in household			0.04*** [0.01]	0.06*** [0.01]	0.06*** [0.01]	0.06*** [0.01]	0.06*** [0.01]
Number of adults 18+ in household				−0.10*** [0.02]	−0.10*** [0.02]	−0.10*** [0.02]	−0.10*** [0.02]
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Central city/suburban status fixed effects	No	No	No	No	No	Yes	Yes
Average heating/cooling degree days controls	No	No	No	No	No	No	Yes
CMSA fixed effects	No	No	No	No	No	No	Yes
Observations	6,885	6,693	6,693	6,693	6,693	6,693	6,693

Notes: Poisson regression. The dependent variable is the duration of stay (in years). Moved into unit in the Summer takes the value 1 if household head moved in the spring or summer (in the previous move). Sample includes all respondents for whom we observe a full duration spell. Robust standard errors in brackets. Central city/suburban status categories: (i) central city of MSA; (ii) inside MSA, but not in central city-urban; (iii) inside MSA, but not in central city-rural; (iv) outside MSA, urban; (v) outside MSA, rural. Heating/cooling degree days categories: (i) Coldest: 7,001+ heating degree days and < 2,000 cooling degree days; (ii) Cold: 5,500–7,000 heating degree days and < 2,000 cooling degree days; (iii) Cool: 4,000–5,499 heating degree days and < 2,000 cooling degree days; (iv) Mild: < 4,000 heating degree days and < 2,000 cooling degree days; (v) Mixed: 2,000–3,999 heating degree days and 2,000+ cooling degree days; (vi) Hot: < 2,000 heating degree days and 2,000+ cooling degree days.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

move and the previous move.) The data correspond to the AHS 1999. Before we describe the results, we would like to highlight three caveats with the data used in this first set of regressions. First, we observe the season in which the household moved into the previous house, but not the season in which s/he actually bought that house; this should not be problematic if the time of purchase and move fall in the same season. (For the latest move, we observe both the season of the move and of the purchase, and the two fall in the same season for most movers, but we do not have similar information for the previous move.) Second, we restrict the sample to households who own the current house, but do not know whether the household owned or rented the previous house. (To the extent that match specificity is more important for owners than for renters, our estimates of the effect of the season on duration will be biased downwards.) Third, the values for all the covariates used as controls in the regressions (described next) correspond to those observed at the time of the survey (in 1999), as we do not observe the past values of these variables.

The results are summarized in Table 4, which shows (Poisson) regressions of the number of years of stay on a dummy variable that takes the value 1 if the household head moved in the summer season. Regressions are weighted by the variable WEIGHT in the AHS, which corresponds to the weight assigned to each case in the sample. As Table 4 shows, on average, the duration of stay increases by 4 to 5 percent when households move in the summer. The results are robust to a number of controls, including the (log) family income (variable ZINC in the AHS), the size of the household (variable PER in the AHS), and the number of people in the household older than 18 (ZADULT), as well as regional fixed effects (REGION), and dummy variables for the urban/suburban/rural status of the location (METRO3) and the heating and cooling degree days (DEGREE). The duration of stay appears

TABLE 5—NUMBER OF REPLACEMENTS AND ADDITIONS AND SEASON IN WHICH MATCH WAS FORMED

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Moved into unit in the Summer	−0.10** [0.05]	−0.11** [0.05]	−0.11** [0.05]	−0.12** [0.05]	−0.12*** [0.05]	−0.12** [0.05]	−0.12** [0.05]	−0.12*** [0.05]	−0.11** [0.04]
(log) year unit was built		−26.32*** [1.80]	−27.84*** [1.86]	−27.70*** [1.88]	−27.71*** [1.88]	−27.79*** [1.88]	−29.16*** [2.00]	−29.37*** [2.05]	−29.09*** [2.10]
(log) family income			0.19*** [0.03]	0.17*** [0.03]	0.18*** [0.03]	0.18*** [0.03]	0.18*** [0.03]	0.19*** [0.03]	0.18*** [0.03]
Number of persons in household				0.04** [0.02]	0.06*** [0.02]	0.04* [0.02]	0.04* [0.02]	0.04* [0.02]	0.04* [0.02]
Number of adults 18+ in household					−0.06 [0.04]	−0.04 [0.04]	−0.04 [0.04]	−0.04 [0.04]	−0.04 [0.04]
Children in school dummy						0.05 [0.06]	0.05 [0.06]	0.05 [0.06]	0.05 [0.06]
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes		Yes
Central city/suburban status fixed effects	No	No	No	No	No	No	Yes		Yes
Average heating/cooling degree days controls	No	No	No	No	No	No	No		Yes
CMSA fixed effects	No	No	No	No	No	No	No		Yes
Observations	5,982	5,982	5,885	5,885	5,885	5,885	5,885		5,885

Notes: Poisson regression. The dependent variable is the number of replacements and alterations within two years after the move relative to the property value. Sample includes all respondents who moved in or after 1997. Moved into unit in the Summer takes the value 1 if household head moved in the spring or summer (in the last move). Robust standard errors in brackets. Central city/suburban status categories: (i) central city of MSA; (ii) inside MSA, but not in central city-urban; (iii) inside MSA, but not in central city-rural; (iv) outside MSA, urban; (v) outside MSA, rural. Heating/cooling degree days categories: (i) Coldest: 7,001+ heating degree days and < 2,000 cooling degree days; (ii) Cold: 5,500–7,000 heating degree days and < 2,000 cooling degree days; (iii) Cool: 4,000–5,499 heating degree days and < 2,000 cooling degree days; (iv) Mild: < 4,000 heating degree days and < 2,000 cooling degree days; (v) Mixed: 2,000–3,999 heating degree days and 2,000+ cooling degree days; (vi) Hot: < 2,000 heating degree days and 2,000+ cooling degree days.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

positively and significantly correlated with the family income and the size of the household (meaning richer and bigger families tend to stay longer in the property) and negatively correlated with the number of adults in the household.

As a second (inverse) proxy for the quality of the match, we consider the number of replacements and additions made to the unit during the first two years after its purchase (variable RAN in the AHS), which we interpret as inversely related to the quality of the original match. In this case, the sample is restricted to households who moved after 1997 for which RAN is reported. We then ask whether the number of replacements and additions depends on the season in which the match was formed. The results are summarized in Table 5, which shows Poisson regressions of the number of replacements and additions on a dummy variable which takes the value 1 if the household head moved in the summer. In addition to the controls used before, in these regressions we can also control for the age of the property, captured by the (log) year in which the house was built (variable BUILD in the AHS), and the presence of school-age children in the family, proxied by a dummy variable taking value 1 if a member of the family attends school.[29] (The dummy is constructed directly from variables SCHPRI, SCHPUB, and SCHOTH in the AHS.) All regressions are weighted by the AHS's variable WEIGHT.

[29] For the duration regressions, we do not observe the age of the previous property, nor the presence of school-age children during the previous duration spell.

Consistent with our hypothesis, we find that the number of replacements and additions is about 10–12 percent lower when the household moved in the summer than when the household moved in the winter. The regression results are robust to the same geographic, house- and household-specific characteristics described above. In particular, the number of replacements and additions increases significantly with the age of the property, the family income, and the number of people in the household. The presence of school-age children does not have a significant effect.

Finally, and related to the previous idea, we use as third proxy the cost of replacements and additions incurred on a house during the first two years after its purchase, which we also interpret as an inverse proxy for the quality of the match. This corresponds to variable RAC in the AHS, which we normalize by the value of the property (VALUE in the AHS). The dependent variable is the logarithm of the RAC-to-VALUE ratio. As before, the sample is restricted to those who bought a house after 1997 and for whom RAC is reported; all regressions are weighted by WEIGHT. The results are described in Table 6. We find that on average, the cost of replacements and additions (relative to the value of the house) are 16 percent lower when the household moved in the summer.[30]

A natural question is whether the lower costs incurred when moving in the summer fully offset the higher prices in the summer. This is not the case, as these costs are only a small share of the property value (the median cost is below 2 percent of the property value). To see this clearly, note that prices plus costs in the summer relative to winter are given by $\frac{P_s + C_s}{P_w + C_w} = \frac{\frac{P_s}{P_w} + \frac{C_s}{P_s}\frac{P_s}{P_w}}{1 + \frac{C_w}{P_w}} = \frac{P_s}{P_w}\frac{1 + \frac{C_s}{P_s}}{1 + \frac{C_w}{P_w}}$.

Replacement and alteration costs relative to the property price are 16 percent lower when the matched is formed in the summer, $\frac{C_s}{P_s} = \frac{C_w}{P_w}(1 - 0.16)$. Since median $\frac{C_w}{P_w} \approx 0.02$, we obtain

$$\frac{P_s + C_s}{P_w + C_w} = \frac{P_s}{P_w}\frac{1 + 0.02 \cdot (1 - 0.16)}{1 + 0.02} = \frac{P_s}{P_w} \cdot 0.997.$$

With price increases of at least 3 percent in the summer, the overall payments made by movers in the summer are still materially higher. (This is consistent with the finding that duration is longer when the match is formed in the summer, suggesting that there are additional gains over and above the cost difference.)

The other significant control is the age of the property, which is positively associated to the costs of replacements and additions relative to the property value.

In all, the microevidence appears to be consistent with the idea that matches formed in the summer tend to be of better quality.

[30] Since the regressions in Table 6 are in logs, the summer effect is obtained as: -16 percent $= [\exp(-0.18) - 1] \times 100$ percent.

TABLE 6—COSTS OF REPLACEMENTS AND ADDITIONS AND SEASON IN WHICH MATCH WAS FORMED

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Moved into unit in the Summer	−0.19*** [0.07]	−0.20*** [0.07]	−0.19*** [0.07]	−0.18*** [0.07]	−0.18*** [0.07]	−0.18*** [0.07]	−0.18** [0.07]	−0.17** [0.07]	−0.18*** [0.07]
(log) year unit was built		−15.13*** [2.76]	−13.79*** [2.84]	−13.79*** [2.84]	−13.80*** [2.84]	−13.63*** [2.84]	−15.99*** [2.88]	−16.49*** [2.87]	−16.36*** [2.92]
(log) family income			−0.12*** [0.04]	−0.10** [0.04]	−0.10** [0.04]	−0.10** [0.04]	−0.06 [0.04]	−0.05 [0.04]	−0.05 [0.04]
Number of persons in household				−0.05* [0.02]	−0.04 [0.03]	−0.01 [0.04]	−0.01 [0.04]	−0.01 [0.04]	−0.02 [0.04]
Number of adults 18+ in household					−0.01 [0.06]	−0.05 [0.07]	−0.05 [0.07]	−0.05 [0.07]	−0.05 [0.07]
Children in school dummy						−0.11 [0.10]	−0.11 [0.10]	−0.11 [0.10]	−0.11 [0.10]
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Central city/suburban status fixed effects	No	No	No	No	No	No	Yes	Yes	Yes
Average heating/cooling degree days controls	No	No	No	No	No	No	No	Yes	Yes
CMSA fixed effects	No	No	No	No	No	No	No	No	Yes
Observations	3,048	3,048	3,015	3,015	3,015	3,015	3,015	3,015	3,015

Notes: The dependent variable is the (log of the) costs of replacements and additions within two years after the move relative to the property value. Sample includes all respondents who moved in or after 1997. Moved into unit in the Summer takes the value 1 if household head moved in the spring or summer (in the last move). Robust standard errors in brackets. Central city/suburban status categories: (i) central city of MSA; (ii) inside MSA, but not in central city-urban; (iii) inside MSA, but not in central city-rural; (iv) outside MSA, urban; (v) outside MSA, rural. Heating/cooling degree days categories: (i) Coldest: 7,001+ heating degree days and < 2,000 cooling degree days; (ii) Cold: 5,500–7,000 heating degree days and < 2,000 cooling degree days; (iii) Cool: 4,000–5,499 heating degree days and < 2,000 cooling degree days; (iv) Mild: < 4,000 heating degree days and < 2,000 cooling degree days; (v) Mixed: 2,000–3,999 heating degree days and 2,000+ cooling degree days; (iv) Hot: < 2,000 heating degree days and 2,000+ cooling degree days.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

III. A Search-and-Matching Model for the Housing Market

We have mentioned that the predictability and size of the seasonal variation in house prices pose a challenge to existing models of the housing market. In the online Appendix we study the canonical models in the literature and argue that they cannot account for the seasonality we see in the data, calling for a different mechanism to explain seasonal patterns. In this section we develop a search-and-matching model for the housing market with two key elements, "match-specific quality" and "thick-market effects." We then show that the model can generate seasonal fluctuations comparable to those in the data.

A. *The Model Economy*

The economy is populated by a unit measure of infinitely lived agents, who have linear preferences over housing services and a nondurable consumption good. Each period agents receive a fixed endowment of the consumption good which they can either consume or use to buy housing services. An agent can only enjoy housing services by living in one house at a time: that is, he can only be "matched" to one house at a time. Agents who are not matched to a house seek to buy one ("buyers").

There is a unit measure of housing stock. Correspondingly, each period a house can be either matched or unmatched. A matched house delivers a flow of housing services of quality ε to its owner. The quality of housing services ε is match-specific, and it reflects the suitability of a match between a house and its owner. In other words, for any house, the quality of housing services is idiosyncratic to the match between the house and the potential owner. For example, a particular house may match a buyer's taste perfectly well, while at the same time being an unsatisfactory match to another buyer. Hence, ε is not the type of house (or of the seller who owns a particular house). This is consistent with our data, which control for houses' characteristics, but not for the quality of a match.[31]

We assume that in a market with many houses for sale, a buyer is more likely to find a better match, what we refer to as the "thick-market effect." As in Diamond (1981), we model this idea by assuming that the match-specific quality ε follows a distribution $F(\varepsilon, v)$, with positive support and finite mean, and

$$F(\cdot, v') \leq F(\cdot, v) \Leftrightarrow v' > v, \tag{1}$$

where v denotes the stock of houses for sale. In words, when the stock of houses v is larger, a random match-quality draw from $F(\varepsilon, v)$ is likely to be higher. The online Appendix to this article provides detailed microfoundations and derivations for this assumption.[32]

Unmatched houses are "for sale" and are owned by "sellers;" sellers receive a flow u from any unmatched house they own, where the flow u is common to all sellers.

B. *Seasons and Timing*

There are two seasons, $j = s, w$ (for summer and winter); each model period is a season, and the two seasons alternate. At the beginning of a period j, an existing match between a homeowner and his house breaks with probability $1 - \phi^j$, and the house is put up for sale, adding to the stock of houses for sales, denoted by v^j. The homeowner whose existing match has broken becomes simultaneously a seller and a buyer, adding to the pool of buyers, denoted by b^j. In our baseline model, the parameter ϕ^j is the only (ex ante) difference between the seasons.[33] We focus on periodic steady states with constant v^s and v^w. Since a match is between one house and one agent, and there is a unit measure of agents and a unit measure of houses, it is always the case that the mass of houses for sale equals the mass of buyers: $v^j = b^j$.

Our objective is to investigate how such deterministic driver of seasonality can be amplified and revealed as seasonality in transactions and prices in the housing

[31] Repeat-sale indexes do not control for the quality of a match, which is not observed by data collectors.

[32] Heuristically, one way to interpret our assumption is as follows. Suppose the buyer samples n units of vacant houses when the stock of vacancies is v. As long as the number of units sampled n increases in v, the maximum match quality ε in the sample will be "stochastically larger." In other words, for any underlying distribution of match quality, the distribution of the maximum in a sample of size n will first-order stochastically dominate the distribution of the maximum in a smaller sample $n' < n$. As such, F can be interpreted as the distribution of the sample maximum. In the online Appendix, we offer rigorous microfoundations for this assumption.

[33] This difference could be determined, for example, by the school calendar or summer marriages, among other factors, exogenous to our model. In the online Appendix we discuss seasonal transaction costs as an alternative driver of seasonality.

market due to the thick-market effects on the match-specific quality. By focusing on the periodic steady state, we are studying a deterministic cycle and agents are aware that they are in such a cycle with ϕ^j, transactions, and prices fluctuating between high and low levels across the two seasons.

During each period, every buyer meets with a seller and every seller meets with a buyer. Upon meeting, the match-specific quality between the potential buyer and the house is drawn from a distribution $F(\varepsilon, v)$. If the buyer and seller agree on a transaction, the buyer pays a price (discussed later) to the seller, and starts enjoying the housing services ε. If not, the buyer looks for a house again next period, the seller receives the flow u, and puts the house up for sale again next period.[34] An agent can hence be either a matched homeowner or a buyer, and, at the same time, he could also be a seller. Sellers also may have multiple houses to sell.[35]

C. *The Homeowner*

The value of living in a house with match quality ε starting in season s is given by:

$$H^s(\varepsilon) = \varepsilon + \beta\phi^w H^w(\varepsilon) + \beta(1 - \phi^w)[V^w + B^w],$$

where $\beta \in (0, 1)$ is the discount factor. With probability $(1 - \phi^w)$ the homeowner receives a moving shock and becomes both a buyer and a seller (putting his house up for sale), with continuation value $(V^w + B^w)$, where V^j is the value of a house for sale to the seller and B^j is the value of being a buyer in season $j = s, w$, as defined later. With probability ϕ^w the homeowner keeps receiving housing services of quality ε and stays in the house. The formula for $H^w(\varepsilon)$ is perfectly isomorphic to $H^s(\varepsilon)$; in the interest of space we omit here and throughout the paper the corresponding expressions for season w. The value of being a matched homeowner can be therefore rewritten as

$$(2) \quad H^s(\varepsilon) = \frac{1 + \beta\phi^w}{1 - \beta^2\phi^w\phi^s}\varepsilon + \frac{\beta(1 - \phi^w)(V^w + B^w) + \beta^2\phi^w(1 - \phi^s)(V^s + B^s)}{1 - \beta^2\phi^w\phi^s},$$

which is strictly increasing in ε. The first term that enters the housing value $H^s(\varepsilon)$ is the effective (adjusted for moving probabilities) present discounted value of staying in a house with match quality ε and the second term contains the values in the event that the match may dissolve in any future summer or winter.

D. *Market Equilibrium*

We focus on the case in which both seller and buyer observe the quality of the match, ε, which is drawn from $F^j(\varepsilon) \equiv F(\varepsilon, v^j)$; we derive the results for the case in which the seller cannot observe ε in the online Appendix. If the transaction goes through, the buyer pays the seller a mutually agreed price, and starts enjoying the

[34] In the online Appendix we relax the assumption that if the transaction does not go through, the buyer and seller need to wait for next period to transact with other agents.

[35] In the online Appendix, we show that the probability of owning multiple houses is quantitatively small.

housing services flow in the same season j. If the transaction does not go through, the buyer receives zero housing services and looks for a house again next season. This will be the case, for example, if buyers searching for a house pay a rent equal to the utility they derive from the rented property—what is key is that the rental property is not owned by the same potential seller with whom the buyer meets. On the seller's side, when the transaction does not go through, he receives the flow u in season j and puts the house up for sale again next season. The flow u can be interpreted as a net rental income received by the seller. Again, what is key is that the tenant is not the same potential buyer who visits the house.

Reservation Quality.—The total surplus of a transaction is

$$S^s(\varepsilon) = H^s(\varepsilon) - [\beta(B^w + V^w) + u]. \tag{3}$$

Intuitively, a new transaction generates a new match of value $H^s(\varepsilon)$; if the transaction does not go through, the buyer and the seller obtain βB^w and $(\beta V^w + u)$, respectively. Since ε is observable and the surplus is transferrable, a transaction goes through as long as the total surplus $S^s(\varepsilon)$ is positive. Given $H^s(\varepsilon)$ is increasing in ε, a transaction goes through if $\varepsilon \geq \varepsilon^s$, where the reservation ε^s is defined by:

$$\varepsilon^s =: H^s(\varepsilon^s) = \beta(B^w + V^w) + u, \tag{4}$$

and $1 - F^s(\varepsilon^s)$ is thus the probability that a transaction is carried out. Since the reservation quality ε^s is related to the total surplus independently of how the surplus is divided between the buyer and the seller, we defer the discussion of equilibrium prices to Section IVB. Using the expression of housing value $H^s(\varepsilon)$ in (2), equation (4) becomes

$$\frac{1 + \beta\phi^w}{1 - \beta^2\phi^w\phi^s}\varepsilon^s = u - \frac{\beta^2\phi^w(1 - \phi^s)}{1 - \beta^2\phi^w\phi^s}(B^s + V^s) + \frac{1 - \beta^2\phi^s}{1 - \beta^2\phi^w\phi^s}\beta\phi^w(B^w + V^w). \tag{5}$$

The Bellman equation for the sum of values is

$$B^s + V^s = \beta(B^w + V^w) + u + [1 - F^s(\varepsilon^s)]\,E^s[S^s(\varepsilon)\,|\,\varepsilon \geq \varepsilon^s], \tag{6}$$

where $E^s[\,\cdot\,]$ indicates the expectation is taken with respect to distribution $F^s(\,\cdot\,)$. The sum of values in season s covers the outside option, $\beta(B^w + V^w) + u$ (the flow u plus the option value of buying and selling next season) and, with probability $[1 - F^s(\varepsilon^s)]$, on the expected surplus from a transaction for sellers and buyers. Solving this explicitly and using the expression for $S^j(\varepsilon), j = s, w$ in (20)

$$B^s + V^s = \frac{u}{1 - \beta} + \frac{(1 + \beta\phi^w)\,h^s(\varepsilon^s) + \beta(1 + \beta\phi^s)\,h^w(\varepsilon^w)}{(1 - \beta^2)\,(1 - \beta^2\phi^w\phi^s)}, \tag{7}$$

where $h^s(\varepsilon^s) \equiv \left[1 - F^s(\varepsilon^s)\right] E\left[\varepsilon - \varepsilon^s \middle| \varepsilon \geq \varepsilon^s\right]$ is the expected surplus of quality above threshold ε^s.

The equilibrium values $\varepsilon^s, \varepsilon^w, (B^s + V^s)$, and $(B^w + V^w)$ in (5) and (7) depend on equilibrium vacancies v^s and v^w, which we now derive.

Stock of Houses for Sale.—In any season s, the law of motion for the stock of houses for sale (and for the stock of buyers) is

$$v^s = (1 - \phi^s)\left[v^w\left(1 - F^w(\varepsilon^w)\right) + 1 - v^w\right] + v^w F^w(\varepsilon^w),$$

where the first term corresponds to houses that received a moving shock and hence were put for sale this season and the second term corresponds to vacancies from last period which did not find a buyer. The expression simplifies to

$$v^s = 1 - \phi^s + v^w F^w(\varepsilon^w)\,\phi^s. \tag{8}$$

The equilibrium quantities $(B^s + V^s, B^w + V^w, \varepsilon^s, \varepsilon^w, v^s, v^w)$ jointly satisfy equations (5), (7), and (8) together with the isomorphic equations for the other season. They are independent of how the total surplus is shared across buyers and sellers: that is, independent of the exact price-setting mechanism. We hence discuss seasonality in vacancies and transactions first, before we specify the particular price-setting mechanism.

IV. Model-Generated Seasonality

In the baseline model, seasonality is driven by the higher moving probability in the summer: $1 - \phi^s > 1 - \phi^w$. As shown earlier, the equilibrium quantities $(B^s + V^s, B^w + V^w, \varepsilon^s, \varepsilon^w, v^s, v^w)$ jointly satisfy six equations. Before jumping directly to the quantitative results we discuss the underlying mechanisms through which a higher probability of relocating in the summer leads to a larger stock of vacancies and a higher expected return for buyers and sellers, i.e., $v^s > v^w$ and $B^s + V^s > B^w + V^w$. Hence, this section aims at making the model's mechanics more explicit.

It is important to reiterate that our notion of seasonality is not a cross-steady states comparison: that is, we are not comparing a steady state with a high probability of moving houses to another steady state with a low probability of moving. Instead, the seasonal values we derive are equilibrium values along a periodic steady state where agents take into account that the economy is fluctuating deterministically between the summer and the winter seasons.

Using (8), the stock of houses for sale in season s is given by

$$v^s = \frac{1 - \phi^s + \phi^s F^w(\varepsilon^w)\,(1 - \phi^w)}{1 - F^s(\varepsilon^s)\,F^w(\varepsilon^w)\,\phi^s\phi^w}. \tag{9}$$

The ex ante higher probability of moving in the summer ($1 - \phi^s > 1 - \phi^w$) clearly has a direct positive effect on v^s, and this effect also dominates quantitatively when

we calibrate the model to match the average duration of stay in a house.[36] Thus, this implies $v^s > v^w$. The probability of moving is exogenous in our model and we calibrate it so as to match the seasonality in vacancies. Our main interest is to predict the seasonality in transactions and prices.

To that aim, we first take a somewhat tedious but useful detour to comment on the seasonality of the sum of values $(B^j + V^j)$. Intuitively, a higher stock of vacancies in the summer implies higher expected returns to a buyer and a seller in the summer because of better matches through the thick-market effect. These higher expected returns in the summer, however, also raise the outside options of a buyer and a seller in the winter. Higher outside options make both the buyer and the seller more demanding and tend to increase the reservation quality in the winter. In equilibrium, however, the overall effect on reservation quality is ambiguous.[37] More formally, the higher stock of vacancies in the summer, $v^s > v^w$, implies a higher expected surplus quality $h^s(\cdot)$ for any given cutoff through the thick-market effects as in (1).[38] Given $\phi^w > \phi^s$, it thus follows from equation (7) that $B^s + V^s > B^w + V^w$ if the two equilibrium cutoffs ε^s and ε^w are close. In other words, the expected return $(B^j + V^j)$ is higher in the summer as long as the thick-market effect dominates a potentially offsetting equilibrium effect from the reservation quality. Quantitatively, the two cutoffs turn out to be close for reasonable parametrizations of the model and hence the thick-market effect indeed dominates.

A. *Seasonality in Transactions*

The number of transactions in equilibrium in season s is given by

$$Q^s = v^s[1 - F^s(\varepsilon^s)]. \tag{11}$$

(An isomorphic expression holds for Q^w.) From (11), it is evident that a larger stock of vacancies in the summer, $v^s > v^w$, has a direct positive effect on the number of

[36] More specifically, the numerator is a weighted average of 1 and $F^w(\varepsilon^w)(1 - \phi^w)$, with $1 - \phi^s$ being the weight assigned to 1 in the equation for v^s. Since $1 - \phi^s > 1 - \phi^w$, the equation for v^s assigns a higher weight on 1. Since $F^w(\varepsilon^w)(1 - \phi^w) < 1$, higher weight on 1 leads to $v^s > v^w$; this is because $F^w(\varepsilon^w)(1 - \phi^w)$ is virtually aseasonal as there are two opposite effects: $F^w(\varepsilon^w) > F^s(\varepsilon^s)$ and $(1 - \phi^w) < (1 - \phi^s)$ that tend to largely cancel each other.

[37] Note, using (4), that lower outside options $(B^w + V^w)$ imply a lower housing value for the marginal transaction in the summer,

$$H^s(\varepsilon^s) < H^w(\varepsilon^w). \tag{10}$$

This does not necessarily imply a lower reservation quality in the summer, $\varepsilon^s < \varepsilon^w$, because the ranking of $H^s(\varepsilon)$ and $H^w(\varepsilon)$ depends on the level of ε. To see this, note from (2), that $H^j(\varepsilon)$ is linear in ε for $j = s, w$. Given $\phi^w > \phi^s$, $H^s(\cdot)$ is steeper than $H^w(\cdot)$. The difference in the intercepts between $H^s(\cdot)$ and $H^w(\cdot)$ is proportional to

$$\beta[(1 - \phi^w)(1 - \beta\phi^s)(B^w + V^w) - (1 - \phi^s)(1 - \beta\phi^w)(B^s + V^s)],$$

which is negative when $B^s + V^s > B^w + V^w$. Therefore, $H^s(\cdot)$ and $H^w(\cdot)$ must cross once at $\hat{\varepsilon}$. Thus if the equilibrium reservation quality in the summer is sufficiently high, $\varepsilon^s > \hat{\varepsilon}$, then $H^s(\varepsilon^s) > H^w(\varepsilon^s)$. Therefore, in order for inequality (10) to hold, we must have $\varepsilon^w > \varepsilon^s$. In this case, a lower outside option in the summer leads to a lower cutoff. On the other hand, if the equilibrium reservation quality in the summer is sufficiently low, $\varepsilon^s < \hat{\varepsilon}$, then $H^s(\varepsilon^s) < H^w(\varepsilon^s)$; in this case, the inequality $\varepsilon^w > \varepsilon^s$ is no longer required for inequality (10) to hold. In sum, the two equilibrium cutoffs cannot be ranked.

[38] To see this, rewrite $h^s(x) = \int_x [1 - F^s(\varepsilon)]\, d\varepsilon$ using integration by parts.

transactions in the summer relative to winter. Furthermore, if the probability of a transaction is also higher in the summer, then transactions will be more seasonal than vacancies. This amplification effect, which follows from the first-order stochastic dominance of $F^s(\cdot)$ over $F^w(\cdot)$, is indeed present in our quantitative exercise.[39] Intuitively, a higher stock of vacancies leads to better matches through the thick-market effect, resulting in a higher transaction probability.[40]

B. *Seasonality in Prices*

As discussed earlier, results on seasonality in vacancies and transactions are independent of the exact price-setting mechanism: i.e., how the surplus is shared between a buyer and seller. Let $S_v^s(\varepsilon)$ and $S_b^s(\varepsilon)$ be the surpluses of a transaction to the seller and to the buyer, respectively, in season s, when the match quality is ε and the price is $p^s(\varepsilon)$

$$S_v^s(\varepsilon) \equiv p^s(\varepsilon) - (u + \beta V^w), \tag{12}$$

$$S_b^s(\varepsilon) \equiv H^s(\varepsilon) - p^s(\varepsilon) - \beta B^w. \tag{13}$$

The value functions for the buyer and the seller in season s are, respectively

$$V^s = \beta V^w + u + \left[1 - F^s(\varepsilon^s)\right] E^s\left[S_v^s(\varepsilon) \,|\, \varepsilon \geq \varepsilon^s\right], \tag{14}$$

$$B^s = \beta B^w + \left[1 - F^s(\varepsilon^s)\right] E^s\left[S_b^s(\varepsilon) \,|\, \varepsilon \geq \varepsilon^s\right]. \tag{15}$$

A seller can count on his outside option, $\beta V^w + u$ (the flow u plus the option value of selling next season) and, with probability $[1 - F^s(\varepsilon^s)]$, on the expected surplus from a transaction for sellers. A buyer counts on her outside option, βB^w (the option value of buying next season), and, with the same probability, on the expected surplus for buyers. The two Bellman equations (14) and (15) describe the incentives of buyers and sellers in any season s. They will only agree to a transaction if they obtain a positive surplus from the exchange. In particular, (14) shows why a seller would agree to sell in the winter season, even though the average price is higher in the summer. A positive surplus in the winter, $p^w(\varepsilon) - (u + \beta V^s) > 0$, already takes into account the potential higher price in the summer and therefore the higher value of being a seller in the summer (V^s).

We now consider the case in which prices are determined by Nash bargaining. The price maximizes the Nash product

$$\max_{p^s(\varepsilon)} [S_v^s(\varepsilon)]^\theta [S_b^s(\varepsilon)]^{1-\theta} \quad s.t. \quad S_v^s(\varepsilon), S_b^s(\varepsilon) \geq 0,$$

[39] As said, there could be an additional effect if the cutoffs are highly seasonal. For example, if $\varepsilon^w > \varepsilon^s$, there will be even lower volume of transactions in the winter. This is because the outside option for both buyers and sellers is to wait and transact in the next season. Therefore, a higher outside option in the winter makes both buyers and sellers more demanding in the winter and hence less likely to transact, yielding an even smaller number of transactions.

[40] Our model predicts higher probability of transactions in the hot season, thus faster sale and shorter average time on the market for both buyers and sellers. Though we do not have high-frequency data on time on the market to assess seasonality, at lower frequencies, average time to sell tends to be shorter when prices are high (see Krainer 2001 and Diaz and Jerez 2013), a relation that is consistent with our mechanism.

where θ denotes the bargaining power of the seller. The solution implies

$$\frac{S_v^s(\varepsilon)}{S_b^s(\varepsilon)} = \frac{\theta}{1-\theta}, \tag{16}$$

which simplifies to (see online Appendix)

$$p^s(\varepsilon) = \theta H^s(\varepsilon) + (1-\theta)\frac{u}{1-\beta}, \tag{17}$$

a weighted average of the housing value for the matched homeowner and the present discounted value of the flow u. In other words, the price guarantees the seller the proceeds from the alternative usage of the house $\left(\frac{u}{1-\beta}\right)$ and a fraction θ of the social surplus generated by the transaction $\left[H^s(\varepsilon) - \frac{u}{1-\beta}\right]$.

The average price of a transaction is

$$P^s \equiv E^s[p^s(\varepsilon)\,|\,\varepsilon \geq \varepsilon^s] = (1-\theta)\frac{u}{1-\beta} + \theta E^s[H^s(\varepsilon)\,|\,\varepsilon \geq \varepsilon^s], \tag{18}$$

which is increasing in the conditional expected surplus of housing services for transactions exceeding the reservation ε^s. Since u is aseasonal, house prices are seasonal if $\theta > 0$ and the surplus to the seller is seasonal. Moreover, the extent of seasonality is increasing in θ. Intuitively, the source of seasonality is coming from higher average match quality in a thicker market. The higher match quality generates higher utility to the buyer. This will show up as a higher price only if the seller has some bargaining power to extract a fraction of the surplus generated from the match. To see this in equations, rewrite $E^s[H^s(\varepsilon)\,|\,\varepsilon \geq \varepsilon^s]$ as the sum of two terms:

$$E^s[H^s(\varepsilon)\,|\,\varepsilon \geq \varepsilon^s] = H^s(\varepsilon^s) + E^s[S^s(\varepsilon)\,|\,\varepsilon \geq \varepsilon^s]. \tag{19}$$

The first term, $H^j(\varepsilon^j)$, the housing value of the marginal transaction, tends to reduce the average price in the summer since $H^s(\varepsilon^s) < H^w(\varepsilon^w)$. The second term, $E^s[S^s(\varepsilon)\,|\,\varepsilon \geq \varepsilon^s]$, is the expected surplus of a transaction, which tends to increase the average price in the summer due to higher match quality. To see this second term more clearly, observe from (3) and (4) that

$$S^s(\varepsilon) = H^s(\varepsilon) - H^s(\varepsilon^s) = \frac{1+\beta\phi^w}{1-\beta^2\phi^w\phi^s}(\varepsilon - \varepsilon^s); \tag{20}$$

thus

$$E^s\left[S^s(\varepsilon)\,|\,\varepsilon \geq \varepsilon^s\right] = \frac{1+\beta\phi^w}{1-\beta^2\phi^w\phi^s}E^s[\varepsilon - \varepsilon^s\,|\,\varepsilon \geq \varepsilon^s].$$

The average housing value will thus be higher in the summer for two reasons. First, the probability of staying is higher in the winter, $\phi^w > \phi^s$. Second, and more important, given the assumption of first-order stochastic dominance, a higher stock of vacancies $v^s > v^w$ increases the likelihood of drawing a higher match quality

$[1 - F^s(\varepsilon)] \geq [1 - F^w(\varepsilon)]$ $\forall \varepsilon$. This generally leads to a higher conditional surplus in the hot season: $E^s[\varepsilon - \varepsilon^s | \varepsilon \geq \varepsilon^s] \geq E^w[\varepsilon - \varepsilon^w | \varepsilon \geq \varepsilon^w]$.[41]

Given that θ affects P^s only through the equilibrium mass of vacancies (recall the reservation quality ε^s is independent of θ), it follows that the extent of seasonality in prices is increasing in θ. Since (18) holds independently of the steady-state equation for v^s and v^w, this result is independent of what drives $v^s > v^w$. Note finally that the extent of seasonality in prices is decreasing in the size of the (aseasonal) flow u.

Comparison to a Standard Asset-Pricing Approach.—It is useful to compare the price mechanism in our setup with that in a standard asset pricing approach. Equation (14) can be compared to the no-arbitrage condition in asset pricing. Substituting the expression for the surplus into (14), we obtain

$$V^s = [1 - F^s(\varepsilon^s)] P^s + F^s(\varepsilon^s)(\beta V^w + u).$$

The equation expresses the value of a seller as a weighted average of the market price P^s and the continuation value $(\beta V^w + u)$, with the weights given, correspondingly, by the probabilities that the transaction goes through or not. Without the search friction, a buyer will always purchase the house at the market price P^s, thus the probability of a transaction is 1. In that case, the value for being a seller is $V^s = P^s$. Moreover, the surplus of a transaction is 0 in a competitive equilibrium (with perfect arbitrage), so the Bellman equation (14) is equivalent to

$$P^s = \beta P^w + u = \beta(\beta P^s + u) + u \Rightarrow P^s = \frac{u}{1 - \beta},$$

and $P^s = P^w$. In other words, without the model's friction, seasonality in moving probabilities ϕ^s will not be transmitted into seasonality in prices.[42]

[41] To see this, rewrite the conditional surplus using integration by parts:

$$E^s[\varepsilon - \varepsilon^s | \varepsilon \geq \varepsilon^s] = \frac{\int_{\varepsilon^s}(1 - F^s(\varepsilon))\, d\varepsilon}{1 - F^s(\varepsilon^s)}. \tag{21}$$

Putting aside the issue of the equilibrium cutoffs ε^s and ε^w (which are quantitatively close), it follows from equation (21) that the conditional surplus is higher in the hot season, $E^s[\varepsilon - \varepsilon^s | \varepsilon \geq \varepsilon^s] \geq E^w[\varepsilon - \varepsilon^w | \varepsilon \geq \varepsilon^w]$, unless the increase in the likelihood of drawing a particular level of match quality ε dominates the sum of the increase in likelihood of drawing all match qualities higher than ε: i.e., unless $\frac{1 - F^s(\varepsilon)}{1 - F^w(\varepsilon)} > \frac{\int_{\varepsilon}(1 - F^s(\varepsilon))\, d\varepsilon}{\int_{\varepsilon}(1 - F^w(\varepsilon))\, d\varepsilon}$. We cannot rule out this possibility in general, but this case does not arise in our calibration exercise. More formally, we could impose a "uniform" stochastic ordering (see Keilson and Sumita 1982) as a sufficient condition to rule out this case. But as said, such assumption is not necessary for obtaining higher prices in the hot season.

[42] Notice that with the search friction, $P^s \neq \frac{u}{1 - \beta}$. From

$$V^s = \beta V^w + u + [1 - F^s(\varepsilon^s)] E^s[S_v^s(\varepsilon) | \varepsilon \geq \varepsilon^s]$$

substitute the expression for V^w and obtain

$$V^s = \frac{u}{1 - \beta} + \frac{[1 - F^s(\varepsilon^s)] E^s[S_v^s(\varepsilon) | \varepsilon \geq \varepsilon^s] + \beta[1 - F^w(\varepsilon^w)] E^w[S_v^w(\varepsilon) | \varepsilon \geq \varepsilon^w]}{1 - \beta^2}$$

where the expected surpluses are strictly positive.

Our price index P^j, $j = s, w$ is the average price of transactions in season j. The seasonality in price indexes, $P^s > P^w$, is due to the thick-market effect, whereby matches are more likely to be better in the hot season (with a higher stock of houses for sale). In what follows we focus on discussing the mechanism from the seller's perspective (a similar argument can be put forward from a buyer's perspective). The price index P^j is not the price that every seller receives. More specifically, consider a seller in the winter who is meeting with a buyer that has a match-specific quality equal to ε. He has to decide whether to sell now at an agreed price or to wait until the summer, where the average price is P^s. Notice that the seller is not comparing P^w to P^s in his decision because what is relevant for him is not the average price P^w but rather $p^w(\varepsilon)$, which is determined between him and the buyer with quality match ε. The equilibrium value functions (14) and (15) ensure that a transaction will take place as long as the surplus is positive. The option of being able to sell at a possibly higher price in the summer has already been incorporated into the equilibrium surpluses (12) and (13), which in turn pin down the equilibrium price $p^w(\varepsilon)$ as in (17). So even though the price of a transaction for a specific ε might be higher in the hot season, it does not follow that a seller will only transact in the summer because of the stochastic nature of ε. By not transacting at $p^w(\varepsilon)$, a seller may end up with an even lower $p^s(\tilde{\varepsilon})$ in the summer if he meets a buyer with a lower match quality $\tilde{\varepsilon}$, or with no transaction at all if the match quality $\tilde{\varepsilon}$ is too low. So the corresponding arbitrage condition for the seller to decide whether to wait until the hot season has to consider both the probability of transacting in the summer and the distribution of the match quality conditional on transacting. In contrast, in a standard asset-pricing model with deterministic seasons, a seller can always transact (with certainty) at market prices. The choice of whether to sell in the current season or in the next depends exclusively on the flow of benefits (or costs) of owning the house for one season relative to the expected seasonal appreciation.

C. *Quantitative Analysis*

In this section we calibrate the model to study its quantitative implications.

Parameter Values.—We assume the distribution of match-quality $F(\varepsilon, v)$ follows a uniform distribution on $[0, v]$. When $v^s > v^w$ (which will follow from $\phi^w > \phi^s$), this implies first-order stochastic ordering, $F^s(\cdot) \leq F^w(\cdot)$.

We set the discount factor β so that the implied annual real interest rate is 6 percent, as calculated by Blake (2011) for the United States. (The rate might be slightly higher for the United Kingdom, though we use the same to ease cross-country comparability.)

We calibrate the average probability of staying in the house, $\phi = (\phi^s + \phi^w)/2$, to match survey data on the average duration of stay in a given house, which in the model is given by $\frac{1}{1-\phi}$. The median duration in the United States from 1993 through 2005, according to the American Housing Survey, was 18 semesters; the median duration in the United Kingdom during this period, according to the Survey of English Housing was 26 semesters. The implied (average) moving probabilities $(1 - \phi)$ per semester are hence 0.056 and 0.038 for the United States and the United Kingdom, respectively. Because there is no direct data on the ex ante ratio

of moving probabilities between seasons, $(1-\phi^s)/(1-\phi^w)$, we use a range of $(1-\phi^s)/(1-\phi^w)$ from 1.1 to 1.5.[43] This implies a difference in staying probabilities between seasons, $\phi^w - \phi^s$, ranging from 0.004 to 0.015 in the United Kingdom and 0.005 to 0.022 in the United States. One way to pin down the level of $(1-\phi^s)/(1-\phi^w)$ is to use data on inventories (or homes for sale), which correspond to the vacancies v^j in our model. The data are available at quarterly frequency for the United States from the NAR (for the United Kingdom, data on vacancies only exist at yearly frequency). Seasonality in inventories was 28 percent during 1991–2012.[44] As will become clear from the results displayed below, the ratio that exactly matches seasonality in US vacancies is $(1-\phi^s)/(1-\phi^w) = 1.25$. The reader may want to view this as a deep parameter and potentially use it also for the United Kingdom, under the assumption that the extent of seasonality in ex ante moving probabilities does not vary across countries.

We calibrate the flow value u to match the implied average rent-to-price ratio received by the seller. In the United Kingdom, the average gross rent-to-price ratio is roughly around 5 percent per year, according to Global Property Guide.[45] For the United States, Davis, Lehnert, and Martin (2008) argue that the ratio was around 5 percent prior to 1995 when it started falling, reaching 3.5 percent by 2005. In our model, the u/P ratio (where P stands for the average price, absent seasonality) corresponds to the net rental flow received by the seller after paying taxes and other relevant costs; it is accordingly lower than the gross rent-to-price ratio. As a benchmark, we choose u so that the net rent-to-price ratio is equal to 3 percent per year (or 1.5 percent per semester), equivalent to assuming a 40 percent income tax on rent).[46] To obtain the value of u, which, as we said, is aseasonal in the data, we use the equilibrium equations in the model without seasonality: that is, the model in which $\phi^s = \phi^w = \phi$. From (18) and (5), the average price and the reservation quality ε^d in the absence of seasonality are (see the online Appendix)

$$P = \frac{u}{1-\beta} + \theta \frac{\left[1-\beta F(\varepsilon^d)\right] E\left[\varepsilon - \varepsilon^d \mid \varepsilon \geq \varepsilon^d\right]}{(1-\beta)(1-\beta\phi)}, \tag{22}$$

and

$$\frac{\varepsilon^d}{1-\beta\phi} = \frac{u + \frac{\beta\phi}{1-\beta\phi}\int_{\varepsilon^d} \varepsilon \, dF(\varepsilon)}{1-\beta\phi F(\varepsilon^d)}. \tag{23}$$

[43] The two surveys mentioned also report the main reasons for moving. Around 30 percent of the respondents report that living closer to work or to their children's school and getting married are the main reasons for moving. These factors are of course not entirely exogenous, but they can carry a considerably exogenous component; in particular, the school calendar is certainly exogenous to housing market movements (see Goodman 1993 and Tucker, Long, and Marx 1995 on seasonal mobility). In all, the survey evidence supports our working hypothesis that the ex ante probability to move is higher in the summer (or, equivalently the probability to stay is higher in the winter).

[44] We use the inventory series provided by NAR. As a measure of seasonality we use, as before, the difference in annualized growth rates in vacancies between broadly defined summers and winters. As an alternative definition of vacancies we also looked at vacant houses' data from the US Census Bureau. Vacancy is computed as the sum of houses for sale at the beginning of the season relative to the stock of houses. The degree of seasonality in this series, using the same metric, is 31 percent.

[45] Data for the United Kingdom and other European countries can be found at: http://www.globalpropertyguide.com/Europe/United-Kingdom/price-rent-ratio.

[46] In principle, other costs can trim down the 3 percent u/P ratio, including maintenance costs and inefficiencies in the rental market that lead to a higher wedge between what the tenant pays and what the landlord receives; also, it might not be possible to rent the house immediately, leading to lower average flows u. Note that lower values of u/p lead to even higher seasonality in prices and transactions for any given level of seasonality in moving shocks.

We hence substitute $u = 0.015 \cdot P$ in the aseasonal model (equivalent to an annual rent-to-price ratio of 3 percent) for $\theta = 1/2$ (when sellers and buyers have the same bargaining power) and find the equilibrium value of P given the calibrated values for β and $F(\cdot)$. We then use the implied value of $u = 0.015 \cdot P$ as a parameter.[47]

Finally, in reporting the results for prices we vary the seller's bargaining power parameter θ from 0 to 1.

The Extent of Seasonality.—Given the calibrated values of u, β, and ϕ discussed above, Table 7 displays the extent of seasonality in vacancies and transactions generated by the model for different values of the ratio of moving probabilities (recall that seasonality in vacancies and transactions is independent of the bargaining power of the seller, θ). As throughout the paper, our metric for seasonality is the annualized difference in growth rates between the two seasons. Column 1 shows the ratio of moving probabilities, $\frac{1-\phi^s}{1-\phi^w}$. Columns 2 and 5 show the implied difference in moving probabilities between the two seasons for the United States and the United Kingdom, $\left[(1-\phi^s)-(1-\phi^w)\right]$. (Recall that, because the average stay in a house differs across the two countries, a given ratio can imply different values for $\phi^w - \phi^s$, as the average probability of stay ϕ differs.) Columns 3 and 4 show the extent of seasonality in vacancies and transactions for an average stay of 9 years (as in the United States) and columns 6 and 7 show the corresponding figures for an average stay of 13 years (as in the United Kingdom).

The first point to note is the large amplification mechanism present in the model: For any given level of seasonality in vacancies, seasonality in transactions is at least four times bigger. Second, the table shows that a small absolute difference in the probability to stay between the two seasons can induce large seasonality in transactions. Third, if we constrain ourselves to $\frac{1-\phi^s}{1-\phi^w} = 1.25$ to match the data on vacancies for the United States, this implies a level of seasonality in transactions of about 115 percent in the United States (the empirical counterpart is 146 percent). For the United Kingdom, ideally we would like to recalibrate the ratio $\frac{1-\phi^s}{1-\phi^w}$ to match its seasonality in vacancies; however, as said, the data are only available at yearly frequency. Using the same ratio $\frac{1-\phi^s}{1-\phi^w} = 1.25$ as a parameter for the United Kingdom would yield a seasonality in vacancies of 25 percent (the difference with the United States is due to the longer duration of stay in the United Kingdom). This in turn would imply a degree of seasonality in transactions of 113 percent (the empirical counterpart is 139). Note that, for a given ratio $\frac{1-\phi^s}{1-\phi^w}$, the model generates more seasonality in transactions in the United States than in the United Kingdom (as in the data) because a given ratio implies a higher difference in moving probabilities $\left[(1-\phi^s)-(1-\phi^w)\right]$ in the United States than in the United Kingdom, as the average stay is shorter in the former.

[47] We also calibrated the model using different values of u for different θ (instead of setting $\theta = 1/2$), keeping the ratio u/P constant. Results are not significantly different under this procedure, but the comparability of results for different values of θ becomes less clear, since u is not kept fixed.

TABLE 7—SEASONALITY IN VACANCIES AND TRANSACTIONS FOR DIFFERENT $\frac{1-\phi^s}{1-\phi^w}$

	Average moving probability: 0.0556 stay of 9 years (US)			Average moving probability: 0.0385 stay of 13 years (UK)		
Ratio of moving probabilities between seasons (1)	Implied seasonal *difference* in moving probabilities (2)	Vacancies (3)	Transactions (4)	Implied seasonal *difference* in moving probabilities (5)	Vacancies (6)	Transactions (7)
1.10	0.005	12%	49%	0.004	11%	48%
1.20	0.010	23%	94%	0.007	21%	93%
1.25	0.012	28%	115%	0.009	25%	113%
1.30	0.014	33%	136%	0.010	30%	133%
1.40	0.019	42%	174%	0.013	38%	171%
1.50	0.022	51%	211%	0.015	45%	207%

Seasonality in prices, as expressed earlier, depends also on the bargaining power of the seller, θ . Figure 7 plots the model-generated seasonality in prices for different θ and $\frac{1-\phi^s}{1-\phi^w}$, assuming an average stay of 13 years (as in the United Kingdom), and Figure 8 shows the corresponding plot for an average stay of 9 years (as in the United States). As illustrated, seasonality increases with both θ and $\frac{1-\phi^s}{1-\phi^w}$. If, as before, we take $\frac{1-\phi^s}{1-\phi^w} = 1.25$ as given, the exercise implies that to match real-price seasonality in the United Kingdom (of about 5.5 percent), the bargaining power coefficient θ needs to be around 0.8 percent. The corresponding value for the United States as a whole, with real-price seasonality of 4.8 percent, is 0.73 percent.[48]

In all, though stylized, the model can generate seasonal fluctuations quantitatively comparable to those in the data. Together with the results from our study of alternative models in the online Appendix and the microevidence supporting the mechanism, we conclude that thick-market effects on quality offer a plausible explanation for the seasonal patterns in the data.

V. Concluding Remarks

Using data from the United Kingdom and the United States, this paper documents seasonal booms and busts in housing markets. It argues that the predictability and high extent of seasonality in house prices cannot be quantitatively reconciled with existing models in the housing literature.

To explain the empirical patterns, the paper presents a search-and-matching model emphasizing two elements of the housing market. The first is a match-specific component: buyers have different idiosyncratic preferences over houses. The second is the notion that in a market with more houses for sale, a buyer is more likely to

[48] A somewhat higher bargaining power of sellers in the United Kingdom appears plausible. First, population density in the United Kingdom is higher than in the United States making land relatively scarcer, and potentially conferring homeowners more power in price negotiations (this should also be true in denser US cities). Second, anecdotal evidence suggests that land use regulations are particularly stringent in the United Kingdom (see OECD Economic Outlook 2005). Finally, as discussed earlier, price seasonality in US cities is positively correlated with price-to-rent ratios (which, within the model, increase with sellers' power).

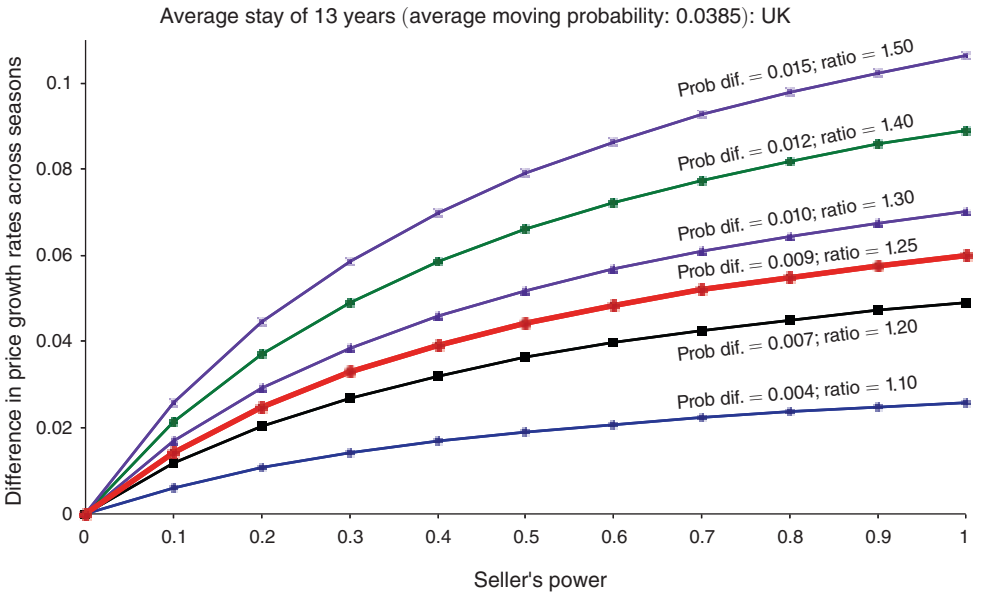

FIGURE 7. SEASONALITY IN PRICES FOR DIFFERENT θ AND $\frac{1-\phi^s}{1-\phi_w}$: UNITED KINGDOM

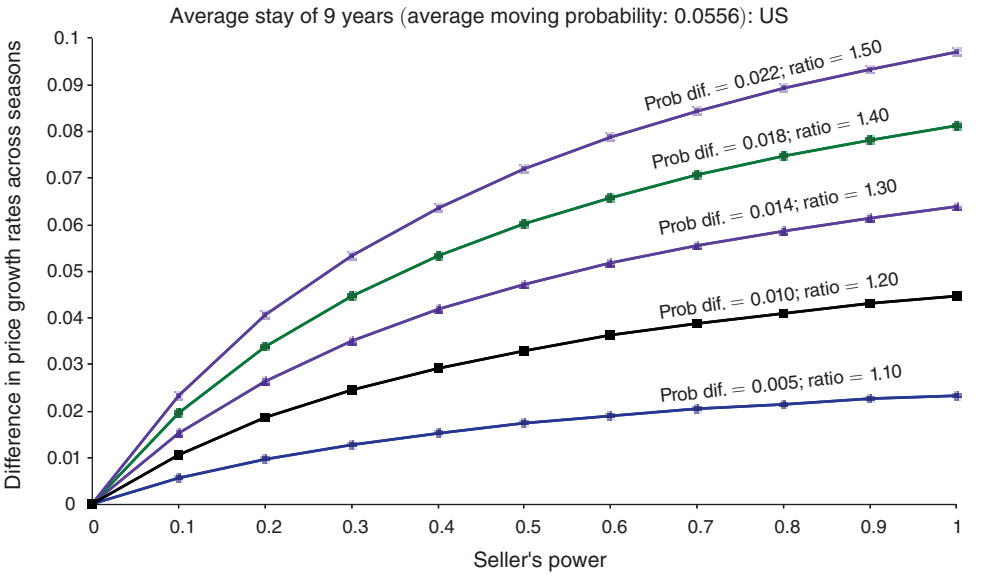

FIGURE 8. SEASONALITY IN PRICES FOR DIFFERENT θ AND $\frac{1-\phi^s}{1-\phi_w}$: UNITED STATES

find a better match, which we refer to as the thick-market effect. With these two elements, the model generates an amplification mechanism such that a small (deterministic) difference in the propensity to relocate across seasons can result in large seasonal swings in house prices and the volume of transactions. When calibrated using data from the United States and the United Kingdom, the model can quantitatively account for most of the seasonal fluctuations in prices and transactions observed in the data. The idea that matches formed in the summer are of better

quality—the idea underlying the model's mechanism—is consistent with empirical evidence presented in the paper.

The model sheds light on a new mechanism governing fluctuations in housing markets that is also likely to operate at lower frequencies. In particular, the thick-market effect at the core of the model's propagation mechanism does not depend on the frequency of the shocks. Lower frequency shocks associated with either business-cycle shocks or with less frequent booms and busts in housing markets could also be propagated through the same mechanism to amplify fluctuations in transactions and prices.

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