Hedging and Pricing Rent Risk with Search Frictions*

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Abstract

The desire of risk-averse households to hedge rent risk is thought to increase home ownership and prices. While evidence for the ownership implication is compelling, support for the price effect is mixed. We show that an important reason is search frictions. Rent risk reduces outside options, leading to less-picky buyers and worse home/buyer matches. This attenuates the rise in the price-to-rent ratio that would otherwise occur without frictions. Consistent with our model, a house remains on the market for fewer days when rent risk is higher. Accounting for frictions significantly increases the effect of rent risk on home prices.

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1. Introduction

An influential theory of the determinants of homeownership involves the desire of risk-averse households to hedge rent risk (Berkovec and Fullerton (1992), Cocco (2000), Ortalo-Magné and Rady (2002), Sinai and Souleles (2005)). Households are short rents in the city where they live and are therefore exposed to rent risk. To the extent that home prices are correlated with rents, owning a home would then be a hedge against rent risk, reducing the variance of a household's wealth. A number of empirical studies find strong evidence that this hedging motive is an important determinant of homeownership.[1] This hedging benefit ought to then be capitalized into home prices. The higher is the rent risk in a city, all else equal, the higher should be the price-to-rent ratio in that city.

However, empirical studies confirming this house-price implication of the hedging motive theory of ownership have been harder to come by. The strongest estimate remains Sinai and Souleles (2005), who finds that a one standard deviation increase in rent risk in a Metropolitan Statistical Area (MSA), measured using the volatility of lagged rent growth, is associated with an increase in the price-to-rent ratio in that MSA of between two to four percent. But subsequent studies have found smaller and more mixed price effects.[2]

An important reason for this dissonance, as we will argue, is that the existing theoretical and empirical work on rent risk assume a frictionless setup where all homes are of a homogeneous quality. But housing markets are characterized by homes of heterogeneous

[1] Sinai and Souleles (2005) find that households who are likely to stay in a high rent risk MSA are 4.2 percent more likely to own a home compared to other households. Banks et al. (2004) find that households who face higher housing price risk should and do own their first home at a younger age, live in larger homes, and be less likely to refinance using comparable panel data from the United States and United Kingdom. Han (2010) finds that rent risk affects the likelihood that existing homeowners to trade up to new homes. Sinai and Souleles (2013) find when the covariance of homes prices are higher across cities that people often move to, they are more likely to own in their present city. Cocco (2000) estimates a structural model of this hedging motive. This is but a few of the leading papers in the literature showing that rent risk is important for home ownership.

[2] Bracke (2015), Melser and Lee (2014), and Dovman et al. (2012) find evidence of this price effect in international markets but back of the envelope calculations suggest that the estimates are smaller than in Sinai and Souleles (2005). In contrast, Hatzvi and Otto (2008) and Lyons and Muellbauer (2015) find no evidence for a rent risk effect on homes prices. This is a fairly comprehensive list of papers on the pricing of rent risk.

quality and search frictions. Recent work on housing search points to the importance of this heterogeneity (Piazzesi et al. (2015), Landvoigt et al. (2015)). For example, hot and cold housing markets across calendar years can emanate from such frictions (Diaz and Jerez (2013), Novy-Marx (2009)). Similarly, the well-documented seasonality within a calendar year in home prices (Case and Shiller (1987), Hosios and Pesando (1991)) and transaction volume, both are higher in spring/summer than fall/winter months, is consistent with time-varying search frictions associated with the school year calendar as households tend to move in the spring/summer (Goodman (1993), Harding et al. (2003), Ngai and Tenreyro (2014)).

In this paper, we show that the effects of this hedging motive on housing markets depend on such time-varying search frictions; in particular, accounting for these frictions is important for accurately measuring the effect of rent risk on prices. Our paper has two parts. The first part is a model where we extend the frictionless theory of the pricing of rent risk to account for search frictions. In the standard frictionless setup, risk-averse households hedge their exposure to rent risk of a homogeneous housing good. In the typical housing search setup, buyers and sellers are risk-neutral and search and bargain over the price of heterogeneous homes taking into account their outside options to continue searching. These outside options are typically exogenously specified.

We integrate these two settings: the need of hedging rent risk and the need of buyers to search for better match quality. To do so, we build a framework based on the over-the-counter asset trading literature (Duffie et al. (2007) and Gârleanu (2009)) and search-and-matching models (Mortensen and Pissarides (1994)). The search for homes by risk-averse households needing to hedge rent risk can be mapped into the standard search framework where households are risk neutral but the outside option of renting is decreasing in rent risk. In other words, we take as given the hedging motive of home ownership, which is well documented in the empirical literature, and see how the price-to-rent ratio varies with rent risk in this framework.

More specifically, we consider a dynamic model where the arrival rate of sellers is characterized by a two state Markov chain: a low arrival-rate-of-sellers state (i.e. high search frictions), which we can map following the literature to fall/winter months, and a high arrival-rate-of-sellers state (i.e. low search frictions), which we can map to spring/summer months. In a search model with homes of heterogeneous quality, we show that the price-to-rent ratio depends on two factors. The first or traditional frictionless factor is that the hedging-against-rent-risk benefits of ownership get impounded into a higher price-to-rent ratio: the higher the rent risk, the higher the price-to-rent ratio. The second or search (matching) factor is that rent risk reduces outside options. This leads to less picky buyers and worse home-buyer matches, attenuating the rise in the price-to-rent ratio that would otherwise occur in a frictionless set-up. That is, the higher the rent risk, the lower is the price-to-rent ratio because of the search factor. The overall effect of rent risk on prices depends on the sum of these two offsetting factors.

Our model's first prediction is regarding days on the market: i.e., the age of the inventory of homes on the market. A higher rent risk, which leads to less picky buyers, should lead to a lower days on the market all else equal. This should be true regardless of the state of the arrival rate; that is, it holds across both spring/summer and fall/winter months. This prediction is new to the literature in that rent risk has not been previously linked to days on the market or housing market liquidity.

Our model's second prediction is that the sensitivity of the price-to-rent ratio to rent risk is higher (i.e. more positive) in the spring/summer months than in the other months. Intuitively, the spring/summer months with a better distribution of potential matches and lower search frictions approximates the frictionless setting. As a result, the first traditional frictionless factor dominates more and we expect a stronger positive relationship between rent risk and price-to-rent ratios. In other words, accounting for search frictions yields a cleaner estimate of the pure effect of the hedging benefits of home ownership on on house prices.

In the second part of the paper, we empirically test these two predictions using Zillow housing data from 2011 to 2016. Our dependent variables of interest are monthly observations of the days on the market and the price-to-rent ratio at the MSA level. Zillow also provides data on monthly rents at the zip code level, which we can then use to create two rent risk measures for each MSA. The first is a cross-sectional measure where we take the standard deviation of monthly rent growth across the zip codes within an MSA. We then average these monthly standard deviations over the previous twelve months to obtain the MSA-level rent risk for a given month. The second is a time-series measure where we take the standard deviation of the monthly rent growth for a zip code using the past twelve months. Then we population weight these standard deviations to obtain the MSA-level rent risk for a given month.

For our days-on-the-market regression, we estimate a panel regression model with the independent variables being the rent risk measure, MSA fixed effects and year-by-month effects. That is, we use within MSA time series variation in these variables of interest that is purged of a common time trend across MSAs flexibly estimated using year-by-month effects. We find that a one standard deviation increase in rent risk leads to a drop in days on the market of roughly 2 days, or a 5% decrease of days on the market relative the unconditional standard deviation of days on the market. The estimate has a t-statistic of about 2 regardless of the rent risk measure used. We consider additional robustness checks such as allowing time-varying effects by Census regions or by the income of MSAs.

We can compare the magnitude of our estimate of the effect of rent risk on days on the market to the existing literature, which has largely sought to quantify how the quality of housing or the talent of the broker affects how long a home remains on the market. Kang and Gardner (1989) find that, holding other characteristics constant, older homes have higher days on market. Using their estimates, one would have to lower the age of a home by 3 years to achieve the same decrease in days on market as we find on average. Haurin (1988) finds that more atypical houses have longer days on market. His estimates suggest that a 30% of a standard deviation increase in his atypicality index moves days on market by about 2 days. He also finds that the size of the real estate brokerage firm that a seller works with lowers days on market. His estimates suggest to get a 2 day decrease in days on market, one would have to have a broker that is 50% larger than the mean in his sample.

For the price-to-rent regression, we estimate a panel regression model with the independent variables being the rent risk measure, the rent risk measure interacted with a dummy variable for hot season (which we define broadly as either the spring and and summer months or more narrowly as May, June, July, August), MSA fixed effects and year-by-month effects.[3] Our results using either the broad or narrow hot season indicators are similar. Like the literature, we assume that there are exogenous differences in search frictions across these periods reflected in the high versus low arrival rate of sellers.

We first replicate the baseline findings of the previous literature. A one standard deviation increase in rent risk is associated with a 4% increase of the price-to-rent ratio relative the unconditional standard deviation of the price-to-rent ratio. The estimate has a t-statistic of 1.8 to 1.9 depending on the rent risk measure used. It is almost identical to the magnitude found by Sinai and Souleles (2005) when they include MSA fixed effects in their regression specification, although we have a more recent sample. We then find that the sensitivity of the price-to-rent ratio to rent risk is significantly larger, almost twice as big, in spring/summer months than other months. The t-statistic for the difference in these sensitivities across the hot versus cold months is around 3.5 to 4. We consider additional specifications to verify the robustness of these results.

Note that these estimates are a lower bound on how much search frictions might offset the effect of rent risk on home prices since there is bound to be nontrivial search frictions even in spring/summer months. In short, accounting for search frictions fundamentally alters the size of the estimates of rent risk on home prices.

Our first contribution is to the hedging-rent-risk literature. Our analysis builds on Sinai and Souleles (2005) by integrating the motive for hedging rent risk into a search framework.

[3]As we detail below in the data section, May, June, July and August are the months with the most housing transactions.

We show that search frictions significantly dampen the capitalization of rent risk into prices and taking account of this dampening leads to an estimate of rent risk on price that is nearly double those found in the previous literature. Our analysis points to the importance of accounting for seasonality in capturing the impact of rent risk on home prices.

Our second contribution is to the literature on the role of search and matching in housing markets (see, e.g., Wheaton (1990), Williams (1995), Krainer (2001), Albrecht et al. (2007)). The recent literature generally focuses on the comovement of prices and sales (for example, Diaz and Jerez (2013), Novy-Marx (2009), Ngai and Tenreyro (2014)). In particular, our work is closet to and builds on Ngai and Tenreyro (2014), who explain house price seasonality in a model with search frictions. A hot season in their model, as in ours, is assumed to have a better distribution of match quality. They show a small driver of seasonality would trigger thick-market effects making it appealing to all other buyers and sellers to transact in the hot season, amplifying seasonality in housing volume. Our model, on the other hand, is interested in how search frictions affect the sensitivity of volume and prices with respect to rent risk. Our empirical analysis suggests that demand side factors of home ownership in the form of hedging demand against rent risk also play a significant role in driving days on the market.

Our paper proceeds as follows. In Section 2, we present our model. In Section 3, we provide the solution and derive the main predictions. In Section 4, we discuss our data. The empirical findings are presented in Section 5. We conclude in Section 6.

2. Model

We consider an economy in which the cost of housing services (i.e., the rent) is uncertain in the spirit of Sinai and Souleles (2005) and house prices are endogenous. Instead of assuming a centralized housing market as in Sinai and Souleles (2005), we allow for a decentralized housing market where buyers have heterogeneous preferences for houses; and more importantly, the market is subject to search frictions. This allows us to provide a link between trading volume (i.e., days on the market), house prices, and rent risk.

Rent Risk There is a unit continuum of households and a unit continuum of houses within a city. All households living in the city require housing. If they do not own a house, they must rent from a rental company. The rent follows an exogenous process, as in Sinai and Souleles (2005)

$$dR_t = \bar{R}dt + \sigma dB_t,$$

where B_t is a standard Brownian motion, $\bar{R}$ is the mean drift in the change of rents, and σ is the volatility of rents, i.e. the rent risk parameter.

In the spirit of the literature, households that do not own the asset must rent, thus being subject to rent fluctuations. The flow utility for an agent who has $A \in \{-1, 0, 1\}$ exposures to rent risk is given by an instantaneous mean-variance utility specification:

$$u(A) \equiv A\bar{R} - \frac{1}{2}r\gamma\left(A^2\sigma^2\right),$$

where r is the instantaneous risk-free rate and $\gamma > 0$ is the risk-aversion coefficient of households. The flow utility for renters, who take one short position of rent is thus given by $-u_R \equiv -\bar{R} - \frac{1}{2}r\gamma\sigma^2$. That is, the flow value of renters is simply the expected rent with adjusted risks. The higher is rent risk, the lower is the flow value since households are risk-averse. Owners, on the other hand, have no exposure to rent risk ($A = 0$). Rental companies, which we do not model, thus have long positions ($A > 0$). For simplicity, we do not allow owners to rent their houses. Only rental companies can provide houses for rent and rented homes are treated as homogeneous goods.

This utility specification is interpreted in terms of risk aversion, borrowed from Duffie et al. (2007) and Gârleanu (2009). Since $\bar{R}$ is the expected rental rate rather than the realized rate, this flow value needs to be adjusted for risk, which is captured by the second term involving γ and σ^2. As established in Duffie et al. (2007), one can obtain this mean-variance utility in an environment where households with CARA preferences trade a risky asset over the counter and choose their consumption optimally to maximize their expected utility. Furthermore, households' value functions and asset prices can be approximately solved in a risk-neutral agent setting using this risk-adjusted utility directly. Applying this result, we can then solve the model with transferable utility, as is standard in search and matching models.

Housing Market Renters are active buyers in the housing market, who seek a house that is suitable for them. The process of searching for a house is costly. The search friction is captured by the Poisson arrival rate at which a buyer can visit a house. We assume that there are two states $z \in \{H, L\}$ that have different arrival rates λ^z, where $\lambda^H > \lambda^L$. A hot season (i.e. spring/summer months) is modeled as the state with a high arrival rate λ^H and thus lower search frictions. A cold season (i.e. fall/winter months) is modeled as the state with a low arrival rate and thus higher search frictions. We further allow the probability of a change in the search friction. Specifically, we assume that the arrival rate follows a continuous-time Markov process with a rate of transition between the two states μ.

After visiting a house, a buyer then finds out his valuation of that house and decides whether to purchase it or keep searching. We assume that the quality of a house is idiosyncratic to the match between the house and potential buyer, which is denoted by h and is drawn from a distribution $F(h)$. Throughout the paper, we assume that the density function is (1) continuously differentiable and (2) log-concave on some interval $[\underline{h}, \bar{h}]$.[4]

If a buyer decides to buy a house with match value h, he then becomes an owner, enjoying a flow value h until he receives a moving (preference) shock. This exogenous moving (preference) shock is a standard assumption in the literature such as in Wheaton (1990).

[4]Log-concavity is a property satisfied by many standard distributions. Commonly-used distributions with log-concave density functions include, for example, uniform, normal, exponential, and extreme value function. See Bagnoli and Bergstrom (2005) for a more complete list. It is only a sufficient set of conditions for our results below.

Specifically, when an owner receives the moving shock, he immediately moves to another location. Moreover, he puts his house for sale, becoming an active seller in the original location. The continuation value in other locations (which we do not model) is normalized to zero for all households.

The utility of an owner with match quality h at state z, denoted by $W^z(h)$, is then given by the following Bellman Equation:

$$rW^z(h) = h + \delta\left(J^z - W^z(h)\right) + \mu(W^{z'}(h) - W^z(h)), \tag{1}$$

where J^z represents the continuation value for a seller and $W^{z'}(h)$ represents the asset value when he switches to the other state z'. The expression can be understood as follows: The flow value of owning house is the quality h. With Poisson rate δ, he becomes a seller with the continuation value J^z. The last term represents the change in the value when switching to the other state z'.

Specifically, the continuation value for a seller yields:

$$rJ^z = \lambda^z \int_{\underline{h}}^{\bar{h}} \max\{p^z(h) - J^z,\, 0\} f(h)dh + \mu(J^{z'} - J^z), \tag{2}$$

where $p^z(h)$ denotes the transaction price for a buyer with matching quality h at state z. The max operator in the integral takes into account that a seller will only sell if the price is higher than the continuation value.

The continuation value for an active buyer (i.e., a renter), denoted by U^z, is given by:

$$rU^z = -u_R + \lambda^z \int_{\underline{h}}^{\bar{h}} \max\{W^z(h) - p^z(h) - U^z,\, 0\} f(h)dh + \mu(U^{z'} - U^z) - \delta U^z, \tag{3}$$

where $-u_R = -\bar{R} - \frac{1}{2}r\gamma\sigma^2$ represents a renter's flow value, as he takes a short position of rents. With arrival rate λ^z, he visits a house, where the match quality h is drawn. A buyer purchases a house if and only if the value of ownership minus the transaction price is larger than his continuation value of searching, which thus explains the max operator in the integral.

The transaction price is determined by Nash bargaining, where sellers' bargain power is given by $\beta \in [0,1]$. Hence, the housing price is given by:

$$\beta(W^z(h) - U^z - p^z(h)) = (1-\beta)(p^z(h) - J^z). \tag{4}$$

Lastly, we assume that, whenever a household moves out the city, he is replaced by a new household who does not own a house (i.e., a renter). Thus, the measure of household in the city remains one. Since there is also a unit measure of houses, the measure of houses for sale must equal the mass of buyers. Let (ν_H, ν_S) denote the measure of matched owners and sellers, respectively. The law of motion of sellers (i.e., the stock of houses for sale) ν_S at state z is then given by

$$d\nu_S^z = \delta\nu_H^z - \lambda^z(1 - F(x^z))\nu_S^z, \tag{5}$$

where the first term corresponds to the houses that received a moving shock and hence were put for sale and the second term corresponds to houses that found a matched buyer.[5]

Reservation Quality Our main subject of interest here is how rent risk affects the transaction price and volume. In particular, as shown in Equations (2) and (3), conditional on visiting a house, a transaction goes through if and only if both parties find it optimal to trade (instead of searching or waiting). That is, the total surplus, denoted by $\Omega^z(h) \equiv W^z(h) - J^z - U^z$, is positive.

Specifically, adding up the value expressions from (1), (2), (3) and making use of the

[5] Similarly, the law of motion of matched owner is then given by $d\nu_H = -\delta\nu_H + \lambda(1 - F(x^z))\nu_B$, where ν_B denotes the measure of buyers, which must equal the measure of sellers (i.e., $\nu_B = \nu_S$).

sharing rule (4), the joint surplus within the pair can be conveniently rewritten as

$$\begin{aligned} r\Omega^z(h) &= r(W^z(h) - U^z - J^z) \\ &= \left(h + \left(\bar{R} + \frac{1}{2}r\gamma\sigma^2\right)\right) - \delta(W^z(h) - U^z - J^z) + \mu(\Omega^{z'}(h) - \Omega^z(h)) - \lambda^z\Sigma^z, \end{aligned} \tag{6}$$

where $\Sigma^z \equiv \int_{x^z}^{\bar{h}} \Omega^z(h)f(h)dh$ represents the average surplus in the market at the state z.

The first term represents the value of the gain from trade for each match h: an owner receives the flow value of h and he saves u_R, since he is no longer subject to rent risk. This shows that the higher the rent risk the higher the surplus.

The second term captures the possibility that an owner needs to resell the house. The third term takes into account the possibility of switching to a different state z'. The last term captures the buyers' and seller's outside options of staying in the market. To see this, when buying a house h, a buyer would give up the possibility of visiting another house, with the expected surplus $\lambda(1-\beta)\Sigma^z$. On the other hand, the expected surplus for a seller to remain in the market is then $\lambda^z\beta\Sigma^z$. This thus explains the last term $\lambda^z\Sigma^z$.

Since $\Omega^z(h)$ is monotonically increasing in h, there is a unique reservation quality x^z that solves $\Omega^z(x^z) = 0$. Hence, a transaction goes through if and only if the quality is higher than the cutoff quality x^z.

Equilibrium A stationary equilibrium can then be characterized by the cutoff quality x^z: a housing price $p^z(h)$ and value function $(W^z(h), J^z, U^z)$ that jointly satisfy Equation (4) and $\Omega^z(x^z) = 0$ for $z \in \{H, L\}$. Furthermore, let (ν_H, ν_S, ν_B) denote the measure of matched owners, sellers, and buyers, respectively. The law of motion of sellers (i.e., the stock of houses for sale) ν_S is then given by $d\nu_S = \delta\nu_H - \lambda(1 - F(x^z))\nu_S$, where the first term corresponds to the houses that received a moving shock and hence were put for sale and the second term corresponds to houses that found a matched buyer. In the steady state, from Equation (5), $\delta\nu_H^z = \lambda^z(1 - F(x^z))\nu_S^z$ and $\nu_H^z + \nu_S^z = 1$.

3. Model Predictions

3.1. Implications for Days on the Market

Our model captures the need of buyers to search for better matching quality in a frictional environment. Our main subject of interest here is how rent risk affects households' searching decisions, which then endogenously determines the aggregate volume (and thus days on the market (DOM)) that we observe. Specifically, a house at state z will then be sold at the rate $\lambda^z(1 - F(x^z))$. Hence, the expected duration of a listing house, which empirically maps to DOM, is then given by

$$DOM^z \equiv \frac{1}{\lambda^z(1 - F(x^z))}.$$

That is, a lower reservation quality x^z (i.e., a less picky buyer) leads to a lower DOM.

DOM is thus determined by the reservation quality x^z. Intuitively, an increase in the rent risk (a higher σ) decreases the outside option of a renter, making him become more desperate and thus more willing to settle for a worse match. This can been seen clearly from Equation (6): fixing any match quality h, an increase in the rent risk increases the trading surplus. Since the reservation quality x^z is such that a buyer is indifferent $\Omega^z(x^z) = 0$, a higher rent risk must then lead to a lower reservation quality x^z, and thus a lower DOM.

Formally, for the sake of illustration, one can consider the simple case where $\mu = 0$, Equation (6) is reduced to

$$(r + \delta)\Omega^z(h) = h + u_R - \lambda^z\Sigma^z,$$

where $u_R = \left(\bar{R} + \frac{1}{2}r\gamma\sigma^2\right)$ increase with rent risk (σ). Observe that $\Omega^z_h(h) = \frac{1}{r+\delta}$. Hence, after integration by parts, the cutoff rule x^z must then solve:

$$0 = x^z + u_R - \left(\frac{\lambda^z}{r + \delta}\int_{x^z}(1 - F(h))dh\right). \tag{7}$$

Thus, the higher rent risk (σ), the lower the cutoff:

$$\frac{\partial x^z}{\partial \sigma^2} = -\frac{r\gamma}{2} \frac{1}{\left\{1 + \frac{\lambda^z}{r+\delta}(1 - F(x^z))\right\}} < 0. \tag{8}$$

Clearly, the cutoff drops more when agents are more risk averse (i.e., a higher γ). In the Appendix, we derive the results for any μ.

Proposition 1. *An increase in rent risk leads to a lower DOM.*

3.2. Rent Risk and Search Friction

We now turn to illustrate how the degree of search frictions (captured by λ) affect traders' acceptance rates. Observe from Equation (7), one can easily see that a higher search friction (i.e., a lower λ^z) decreases the cutoff rule. Intuitively, buyers are less picky when finding the next house visit is hard. This thus shows the level effect of search frictions: lower search frictions lead to a higher cutoff (i.e., a more picky buyer) $x^H > x^L$.

Moreover, search frictions also affect the sensitivity of the cutoff respect to rent risk. To understand this, imagine an extremely "frictional" environment where it is impossible to find next house $\lambda^z \to 0$ or agents are extremely impatient $r \to \infty$. In either case, the effect of the last term in Equation (7) goes to zero, which thus suggests that the cutoff and the rent risk must move one to one in the sense that the sum of this two must be close to zero: $\{x^z + u_R\} \to 0$.

On the other hand, in an environment with lower search frictions, an agent's continuation value of searching matters more. This is captured by the last term: an increase in the cutoff x^z now also increases his continuation value by $\frac{\lambda^z}{r+\delta}(1 - F(x^z))$. This thus shows that the cutoff must move less in an environment with lower search friction, formalized by Lemma 1

Lemma 1. *The cutoff drops less with lower search frictions (i.e., in the high arrival rate* *state λ^H of house visits than in the low arrival rate state λ^L of house visits):*

$$\frac{\partial x^H}{\partial \sigma^2} - \frac{\partial x^L}{\partial \sigma^2} < 0.$$

Notice that the change in the selling rate (i.e., the inverse of DOM), however, depends on both the arrival rate λ^z and the change in the cutoff. That is

$$\frac{\partial \lambda^z (1 - F(x^z))}{\partial \sigma^2} = -\lambda^z F'(x^z) \frac{\partial x^z}{\partial \sigma^2}.$$

Thus, while the cutoff moves less in the hot season, any movement will be amplified by the higher arrival rate λ^H. If the difference in the arrival rate dominates the force of the cutoff movement, one would then observe a larger change in the selling rate during the hot season. As such, our model does not have a definitive prediction regarding how the relationship of DOM and rent risk varies with the season.

3.3. Implications for Price-to-Rent Ratios

But our model does have a clear prediction regarding how the price-to-rent ratio and rent risk varies with the season. Given Equation (4), the price for each individual transaction yields for $\mu = 0$ yields

$$\begin{aligned} p^z(h) &= \beta(W^z(h) - U^z) + (1-\beta)J^z && (9) \\ &= \beta\left(\frac{h + u_R - \lambda^z \Sigma^z}{r + \delta}\right) + J^z. && (10) \end{aligned}$$

Hence, the average price is given by:

$$\begin{aligned} P^z &\equiv \mathbb{E}[p^z(h) | h \geq x^z] && (11) \\ &= \frac{\beta u_R}{r + \delta} + \frac{\beta \mathbb{E}[h | h \geq x^z]}{r + \delta} + \frac{\beta \delta \lambda^z \Sigma^z}{r(r + \delta)}. && (12) \end{aligned}$$

The first term is the traditional frictionless capitalization of rent risk into prices due to the hedging benefits of home ownership. Notice that the higher is rent risk σ^2, the higher is the price, and hence the higher is the price-to-rent ratio since we are holding fixed rent.

The second term captures the average quality conditional on the transaction taking place and represents the quality of the match in the market. Since the rent risk decreases the cutoff, an increase in rent risk leads to worse home-buyer matches, thereby attenuating the rise in the price-to-rent ratio that would otherwise occur in a frictionless set-up. However, since the rent risk increases the total surplus, the price must increase in rent risk. Thus, the offsetting effect, however, will not overturn the standard effect.

Furthermore, according to Lemma 1, the cutoff drops less with lower search frictions, suggesting a smaller matching effect. Hence, as established in the Proposition 2 below, the sensitivity of price with respect to rent risk is higher for hot seasons. This result holds for any μ.

Proposition 2. *For a small moving probability (δ), the sensitivity of the price-to-rent ratio with respect to rent risk is higher with lower search frictions, i.e.* $\frac{dP^H}{d\sigma^2} - \frac{dP^L}{d\sigma^2} > 0$.

Proposition 2 is the basis of our empirical work below on connecting rent risk to price-to-rent ratios. Notice that for the sensitivity of the price-to-rent ratio to rent risk analysis, the prediction is that rent risk leads to a higher price-to-rent ratio in the high arrival state, proxied by the spring/summer months, than the low arrival state, proxied by fall/winter months.

We have not emphasized other more standard predictions of our model that are unconnected to rent risk. First, the price-to-rent ratio should be higher and days on the market lower in the high arrival states (spring/summer months) than low arrival states (fall/winter months). These predictions have already been carefully derived and studied in earlier work such as Ngai and Tenreyro (2014).

4. Data and Variable Construction

To empirically test our model, we need data on rents, house prices and other housing market conditions for MSAs over time. Monthly rents come from Zillow, which provides the median rental price per square foot of rental units at three levels of aggregation: zip code, county and MSA. Monthly house prices also come from Zillow; again we use the median home price per square foot at these three levels of aggregation. At the MSA level, we then have a panel of these data for 236 MSAs from December 2011 to March 2016.[6]

Using these two data series, we construct the monthly *Price to Rent Ratio* of each MSA. We also calculate for each MSA *Days on Market* using Zillow data. Measured monthly at the MSA level, it is the median number of days that listings of homes that month have been on the market. This age of inventory variable in the Zillow database is only available at the MSA level.[7] [8]

We also use the rent data to create two measures of rent risk. The first is what we call the *Cross-Sectional Rent Risk* measure. For each month in the sample, we first adjust our zip code level rent measure to create a measure of real rent per square foot for each zip code by using the CPI (excluding shelter). We then calculate the log change in real rent for a zip code from month *t-1* to month *t*. Finally, we calculate for each MSA the standard deviation of log changes in real rent for the month across the zip codes in that MSA. For each month for our sample of MSAs, we then calculate the simple average of this monthly cross-sectional rent risk measure for the previous 12 months. This is risk measure is expressed in percentage

[6]This is not a balanced panel. For the early months of our sample, 32 MSAs have missing rent or home price information. Our results are qualitatively quite similar to what we present below if we only include MSAs with complete rent and home price data over the entire sample.

[7]This data series only starts in January 2012 and has sparser coverage of MSAs than the Zillow rent and housing price data. Therefore, our analyses using this data will have fewer observations than the rest of the analysis. We obtain qualitatively similar results to those presented below when we constrain our sample for all our analyses to MSAs with this information.

[8]Zillow also has similar but different variable called the days on Zillow that measures the median days on market of homes sold within a given month. The issue of this variable is that it conditions on sold homes as opposed to also homes that did not sell. Our model's DOM quantity can be best thought of applying to all listings. In any event, we obtain qualitatively similar results to those presented below when we use the days on Zillow instead of the age of inventory. These results are available from the authors.

points.

Our second rent risk measure is what we call the *Time-Series Rent Risk* measure. To calculate this, we again use the log change in real rent for each zip code. We then compute for each zipcode the standard deviation of its real rent growth over the previous 12 months. We take the average of this time-series standard deviation for all of the zip codes in a county (equally-weighted). Then we take a population-weighted average of this county measure for all the counties in a MSA. This risk measure is also expressed in percentage points.

Our *Time-Series Rent Risk* is close in spirit to the previous empirical rent risk measure of Sinai and Souleles (2005), but we have fewer years of data compared to them. That motivates our use of the *Cross-Sectional Rent Risk* measure, which economizes on data by simply using the cross-sectional dispersion in rent growth across the zip codes of an MSA in a given month. The latter measure can be thought of as capturing a common factor of rent risk at the MSA level that can be captured by the cross-sectional dispersion in rent growth.

Table 1 presents summary statistics for these data. House prices are on average about 11 times average rents in our sample. The standard deviation of the price-to-rent ratio is 2.38. The inventory of houses up for sale at a point in time has been on the market on average about 84 days with a standard deviation of around 25 days. The mean *Cross-Sectional Rent Risk* is 64 bps per month with a standard deviation of 29 bps. Annually, this would translate to a 2.2% annual rent risk. The mean *Time-Series Rent Risk* is higher, at almost 1% monthly, which would translate to around 3.5% annually. But notice that there is a large tail in that the maximum *Time-Series Rent Risk* is 4.66% monthly, which would be almost 16.1% annually.

We also measure how variable these measures are over time within a MSA. We create transition matrices that measure how likely a MSA moves substantially across the distribution of the measures shown in Table 1 year to year. That is, for each measure, we calculate the average value for each MSA in our sample each calendar year. We then classify each MSA/year observation into quartiles and calculate the probability that a MSA i observed in quartile j in year t is observed in year $t+1$ in the four quartiles of the distribution.

These matrices are shown in Table 2. In Panels A and B, we show the transition probabilities of the two rent risk measures. Not surprisingly, there is persistence over time in these measures. The probabilities along the diagonal of the matrix are always substantial, but they are not one. Even breaking up the rent risk distributions only into coarse quartiles, we see movement of MSAs over time. Panels C and D show the similar transition probabilities for *Price to Rent* and *Days on Market*. There is less movement across quartiles for these measures compared to the rent risk measures, especially for *Price to Rent*, but again the main diagonals are not one.

We next measure the seasonality of our housing market measures and relate them to the literature. We regress the housing market measure on an indicator for various times in the calendar year, year effects and MSA fixed effects. The coefficient on the times in the calendar year indicator measures how the observations of that housing measure differ on average compared to the rest of the calendar year.

Our first method of breaking up the calendar year is taken from Ngai and Tenreyro (2014). They classify the 2nd and 3rd quarter of the calendar year (April, May, June, July, August and September) as the hot season for the housing market. The remainder of the year is the cold season. Figure 1 shows why this is a reasonable way to break up the calendar. It shows the average monthly home sales transaction volume from a couple of sources. Panel A shows the monthly average number of single-family home sales from 1989 to 2016 collected by the National Association of Realtors. June, which is the month with the highest number of transactions, has on average around 450,000 homes sold. Panel B shows a similar measure using the Zillow home sales database from 2009 to 2015. Recall Zillow only has a subset of the transactions in the market. June has in the Zillow data around 150,000 homes sold. But the story is the same using either data source; transactions are on average substantially higher during the middle of the calendar year compared to the ends.

We also construct a second method of breaking up the calendar year. As shown in Figure

1, the beginning and ending month (April and September) of the Ngai and Tenreyro (2014) measure of the hot season has on average substantially fewer transactions compared to the rest of the hot season. So we create a narrower measure of the hot season that omits April and September from the definition.

The results of these OLS regressions are presented in Table 3. We first examine the seasonality of the monthly cross-sectional rent risk measure.[9] In column (1), we measure how this rent risk measure differs in the broadly defined *Hot Season* compared to the rest of the year. The coefficient on the *Hot Season* indicator is negative, but it is very small in magnitude and not statistically different from zero. So on average, there is little difference in the monthly cross-sectional risk measure in the broadly defined hot season compared to the rest of the year. In column (2), we use our narrow definition of the hot season instead. The conclusion is the same; there is no seasonality in the cross-sectional rent risk measure. Finally, we add to the regression specification indicators for every month in the calendar year. Rather than show the coefficients of this regression in a table, we graph them. Figure 2 (Panel A) shows that the monthly rent risk measure is very stable over the calendar year on average. All of our analyses suggest that there is little calendar year cyclicality to our monthly cross-sectional rent risk measure.

In the subsequent columns of Table 3, we similarly examine the seasonality of *Price to Rent* and the *Days on Market*. In columns (3) and (4), there is no evidence that *Price to Rent* is different in the hot season compared to the rest of the year. But in Panel B of Figure 2, where we show the graph of the month coefficients, there is some evidence that that *Price to Rent* rises over the calendar year. This seasonality is different than the results of earlier work such as Case and Shiller (1987) or Ngai and Tenreyro (2014), who find that prices rise during the hot season. We believe that our different finding is mostly being driven by the fact that on average MSA price to rents were increasing relatively steadily over our short sample period. Therefore, later observations (even within a calendar year) on average would

[9] In our subsequent empirical analysis, we will be using an average of lagged rent risk measured over the past year, but for this cursory analysis we want to examine the monthly rent risk seasonality.

have higher values than earlier, masking other seasonalities that might be revealed with a longer data set.

For *Days on Market*, there is more evidence of a seasonality within a calendar year cycle. There is on average a substantial dip in the days on the market during the hot season (using either measure) relative to the rest of the year, which is consistent with the literature. The coefficient on the broad hot season indicator is -20 with a t-statistic of -22. This big difference between spring/summer and the rest of the months can be easily seen in Panel C of Figure 2.

5. Empirical Methodology and Results

In this section, we empirically examine the relationship between rent risk and housing outcomes. We first test Proposition 1, which states that days on the market should fall with rent risk. This establishes the underlying mechanism that a higher rent risk leads to less picky buyers. We then test Proposition 2, which states that the price to rent should increase more with rent risk in the hot season than the other parts of the year. Notice from our summary statistics that there is not a lot of seasonality in either rent risk or the price to rent ratio to begin with in our sample. So the seasonality of the sensitivity of price to rent to rent risk is not being mechanically driven by a seasonality in housing markets per se.

5.1. Days on Market

We first measure how rent risk affects how long houses are on the market. Our empirical strategy involves examining how days on market changes in a MSA over time as our measures of rent risk change in the MSA. Specifically, we estimate OLS regressions of the following form using MSA-level data from December 2011 to March 2016:

$$Days\ on\ Market_{i,t} = \alpha + \beta_1 Rent\ Risk_{i,t} + Year \times Month\ Effects \\ + MSA\ Fixed\ Effects + \epsilon_{i,t}, \quad (13)$$

where $Rent\ Risk_{i,t}$ is the measure of rent risk for MSA i in $year \times month\ t$, $Year \times Month$ Effects is a full set of dummy variables for each month in the sample, and MSA Fixed Effects is a full set of dummy variables for each MSA in the sample. $\epsilon_{i,t}$ is an error term. The coefficient of interest is β_1. It measures the sensitivity of housing outcomes in a MSA to the rent risk in that MSA. Because we have included year-by-month fixed effects and MSA fixed effects in the regression specification, β_1 is identified by changes over time in the rent risk in a MSA that are different than the national trend.

The results are presented in Table 5. In column (1), we show that the cross-sectional rent risk measure on average has a negative and statistically significant effect on *Days on Market*. The magnitude of the coefficient implies that a one standard deviation increase in rent risk (0.29) lowers *Days on Market* by $4.441 \times 0.29 = 1.29$ days. This is about 5.1 percent of the standard deviation of *Days on Market*.

In column (2), we augment the year by month effects to allow these to vary by the income quartile of the MSA. In other words, we are allowing the flexibly estimated time trend (which was previously at the national level) to vary by the income quartile of the MSA. The coefficient on rent risk is -5.184 and similarly to the result in column (1). In column (3), we augment the year by month effects to allow these to vary by Census Regions. The coefficient on rent risk and overall statistical significance are similar to column (1). These three columns tell us that our findings are robust to a number of alternative explanations having to do with time trends that vary by different parts of the population. Given that this prediction and finding is new to the literature, we do not know of an obvious alternative explanation driving this relationship.

In column (4), we just focus on the large MSA defined as the top quartile of MSAs in terms of population. Our motivation for this subsample comes below when we look at how rent risk affect the price-to-rent ratio. Our benchmark there will be Sinai and Souleles (2005) who study a subsample of large MSAs. Here, we want to verify that the effect of rent risk on days on the market remains strong in this subsample, which is indeed the case.

In columns (5)-(8) of Table 5, we show the estimates using the same specifications except the *Time-Series Rent Risk* measure is used instead of the cross-sectional version. The pattern of estimates is very similar. In column (4), the overall effect of rent risk on *Days on Market* is negative; the magnitude of the coefficient suggests that a one standard deviation increase in rent risk lower *Days on Market* by about 0.96 days, or about 3.8 percent of the standard deviation of *Days on Market*. This 3.8 percent figure is very close to the 5 percent figure we obtained using the cross-sectional rent risk measure.

This finding is independent of the well-established fact that days on the market is lower in the summer. We are effectively looking at how days on the market varies unconditionally across a year depending on the rent risk measured in the previous year. In omitted tables, we find that the the effect of rent on days on the market is stronger in the hot season. But we omit this table since our model does not have definitive prediction on this quantity as it is also directly affected by well-document seasonality in days on the market.

5.2. Price to Rent

We next measure the effect of rent risk on the price-to-rent ratio, allowing the effect to vary over the calendar year. Our regression specification is given by:

$$\begin{aligned} Price\ to\ Rent_{i,t} = \alpha + \beta_1 Rent\ Risk_{i,t} + \beta_2 Calendar\ Indicator_t \\ + \beta_3 Rent\ Risk_{i,t} \times Calendar\ Indicator_t \\ + Year \times Month\ Effects + MSA\ Fixed\ Effects + \epsilon_{i,t} \end{aligned} \tag{14}$$

where $Calendar\ Indicator_t$ is a dummy variable for the observation being in a certain part of the year (the broad and narrow definition of the hot season), and the other variables are the same as before. The coefficient of interest is β_3. It measures whether the sensitivity between rent risk and the housing outcomes is different during the hot season compared to the rest of the year.

Column (1) of Table 5 shows the regression results using the cross-sectional rent risk measure. The coefficient on rent risk is positive and statistically different than zero, implying that higher rent risk increases the price-to-rent ratio of a MSA. The magnitude of the coefficient suggests that a one standard deviation increase in the cross-sectional rent risk measure (0.29) increases the price to rent of a MSA by $0.348 \times 0.29 = 0.10$.

In column (2), we measure whether this sensitivity of price to rent to rent risk is different in the broad measure of the hot season compared to the rest of the year. The coefficient on the interaction of the rent risk measure and the spring/summer indicator is positive and statistically different than zero, indicating that the sensitivity of price to rent to rent risk is higher in the spring/summer. The estimates imply that a one standard deviation increase in rent risk (0.29) increases price to rent in a MSA in the hot season by $0.414 \times 0.29 = .12$. This is about 5.0 percent of a standard deviation of price to rent. The coefficients in column (2) suggest that the sensitivity of *Price to Rent* to changes in rent risk is about 41% higher in the hot season than the rest of the year. We find similar results in column (3) when we use the narrower definition of the hot season. The sensitivity of *Price to Rent* to changes in rent risk is about 36% higher in the hot season compared to the rest of the year using this alternative definition of the hot season.

We also allow the sensitivity of rent risk to vary each calendar month. Rather than show the monthly coefficients in a table, we graph them in Panel A of Figure 3. We also plot the standard error bands for our monthly estimates. Again, the sensitivity of rent risk is substantially higher in the spring/summer months compared to the rest of the year. If we compare the months with the highest sensitivity to rent risk (May/June) to the cold season months, the sensitivity in May/June is 50% higher. As far as statistical significance, May/June differ from other months earlier in winter (January/February) or later in the fall (November/December). Our model is simple in terms of allowing for probabilistic switches between hot and cold seasons and hence cannot speak to the monthly variations within a season. But the fact that May and June are the hottest months is intuitive and reasonable since these are often the busiest months in terms of housing transactions as we showed above.

In columns (4) through (6) of Table 5, we repeat the analysis using our *Time-Series Rent Risk* measure instead of the cross-sectional version. The pattern of results is very similar. In column (4), the effect of rent risk on price to rent is positive and marginally statistically significant from zero. The coefficient implies that a one standard deviation increase in rent risk (0.43) increases price to rent in a MSA by $0.165 \times 0.43 = .071$. This is about 3 percent of a standard deviation of price to rent.

In column (5), again we find that the sensitivity of rent risk is higher in the hot season using the broad measure. The interaction term is positive and statistically different from zero, suggesting that a one standard deviation increase in rent risk in the summer increases price to rent by $0.243 \times 0.43 = 0.10$. This is about 4.4 percent of a standard deviation of price to rent. The sensitivity of *Price to Rent* to changes in rent risk is about 102% higher in the hot season than the rest of the year.

For the narrow measure of the hot season in column (6), we find similar results; the sensitivity of *Price to Rent* to changes in rent risk is about 84% higher in the hot season than the rest of the year. The conclusion that the sensitivity of rent risk is higher in the summer is also found when we allow the sensitivities to vary every calendar month (Panel B of Figure 3). The highest sensitivity month (July) is 140% higher than in the cold season months.

5.3. Alternative Explanations and Relation to Estimates in the Literature

In Table 6, we modify our regression specifications to account for alternative explanations and to better relate our estimates of the effect of rent risk on the price-to-rent ratio to those in the literature. We use the broad definition of hot season, but the results are similar if we use the narrow definition. As in our days on the market specification, in columns (1) and (2) using the cross-sectional rent risk measure and columns (4) and (5) using the time series measure, we augment the year by month effects to allow these to vary by the income quartile of the MSA and by the Census Region of the MSA, respectively. The coefficients are similar to the baselines ones in Table 5.

In columns (3) and (6), we just focus on the large MSA defined as the top quartile of MSAs in terms of population. Our regression specification here is closest to the result presented in column 2 of Table III of Sinai and Souleles (2005). They find that a one standard deviation increase in their measure of rent risk increases the price-to-rent ratio of a MSA by about 1.3 percent, which is about a 4.6 percent increase relative to the standard deviation of price to rent in their data. Our baseline estimate is similar to theirs, but we find that the effect of rent risk is higher in the summer. Using the cross-sectional rent risk measure, we find that the effect of rent risk is 1.3 times stronger in the summer in large MSAs.

Using the time series rent risk measure in column (6), the effect of rent risk on price-to-rent is 3.6 times stronger in the summer. That is, accounting for seasonality is important in measuring the sensitivity of the price-to-rent ratio to rent risk. As we discussed in the Introduction, these summer estimates are probably a lower bound on how much search frictions might offset the effect of rent risk on home prices. We know from the literature that there is nontrivial search frictions even in spring/summer months. As such, fully accounting for search frictions is likely to fundamentally alter the size of the estimates of rent risk on home prices. We leave this full accounting for future work.

6. Conclusion

An influential theory of homeownership is the desire of risk averse households to hedge rent risk. Existing theory and empirical work assumes a frictionless set-up where all homes are homogeneous quality. But housing markets are characterized by homes of heterogeneous quality and search frictions. We integrate these two settings: the need of hedging rent risk and the need of buyers to search for better match quality. We show that the price-to-rent ratio depends on two factors. The first or traditional frictionless factor is that the hedging-against-rent-risk benefits of ownership gets impounded into a higher price-to-rent ratio. The second or search (matching) factor is that rent risk reduces outside options.

We develop a series of predictions and empirical specifications to demonstrate the importance of this off-setting search factor that attenuates the sensitivity of price to rent to rent risk. In particular, our model predicts that higher rent risk should lead to a lower days on the market, which we find very strongly in the data. In doing so, we have reconciled a dissonance in this important literature of why there is such robust evidence for the hedging motive of homeownership and so little for the pricing of rent risk.

A. Appendix

A.1. Derivation for the Cutoff Value

Given that $\Omega^z(h) = W^z(h) - J^z - U^z$, we have

$$r\Omega^z(h) = (h + u_R) + \delta(J^z - W^z(h) - U) + \mu(\Omega^{z'}(h) - \Omega^z(h)) - \lambda^z\Sigma^z, \tag{A.15}$$
$$= (h + u_R) - \delta\Omega^z(h) + \mu(\Omega^{z'}(h) - \Omega^z(h)) - \lambda^z\Sigma^z,$$

where $\Sigma^z \equiv \int_{x^z}^{\bar{h}} \Omega^z(h)dF(h)$.

The simple comparative statics suggests that the cutoff must be lower in the cold season: $x^L < x^H$. The surplus for some quality $h \in [x^L, x^H]$ is positive only at the low state but not at the high state. From Equation (A.15), $\Omega^L_h(h) = \frac{1}{r+\delta+\mu}$, for $h \in [x^L, x^H]$.

For any $h \geq x^H$, the surplus is positive for both states. We have

$$(r + \delta + 2\mu)\left(\Omega^z(h) - \Omega^{z'}(h)\right) = -(\lambda^z\Sigma^z - \lambda^{z'}\Sigma^{z'}) \tag{A.16}$$

Equation (A.15) implies $\Omega^z_h(h) = \Omega^{z'}_h(h) = \frac{1}{r+\delta}$, for any $h \geq x^H$.

The solution $\{x^L, x^H\}$ are then jointly determined, which solves $\Omega^z(x^z) = 0$ for $z \in \{H, L\}$. Furthermore, the total surplus Σ^z for each state depends on the cutoffs. Given $\Omega^z_h(h)$, after integration by part, we have

$$\Sigma^L(x^L, x^H) = \frac{1}{r + \delta + \mu}\int_{x^L}^{x^H}(1 - F(h))dh + \frac{1}{r + \delta}\int_{x^H}(1 - F(h))dh, \tag{A.17}$$

and

$$\Sigma^H(x^L, x^H) = \frac{1}{r + \delta}\int_{x^H}(1 - F(h))dh. \tag{A.18}$$

Hence, for low state, $\Omega^L(x^L) = 0$ implies:

$$0 = x^L + u_R - \lambda^L\Sigma^L, \tag{A.19}$$

where $\Omega^H(x^L) = 0$, since $x^L < x^H$. For high state, $\Omega^H(x^H) = 0$ implies:

$$0 = x^H + u_R - \lambda^H \Sigma^H + \mu \left(\frac{x^H - x^L}{r + \delta + \mu} \right). \tag{A.20}$$

Hence, $\{x^L, x^H\}$ must solve the following system of equations:

$$K(x^L, x^H, u_R) \equiv x^L + u_R - \lambda^L \Sigma^L(x^L, x^H) = 0, \tag{A.21}$$

and

$$G(x^L, x^H, u_R) \equiv \left(x^H - x^L\right) \left(\frac{r + \delta + 2\mu}{r + \delta + \mu} \right) - \left(\lambda^H \Sigma^H(x^L, x^H) - \lambda^L \Sigma^L(x^L, x^H)\right) = 0. \tag{A.22}$$

Note that Equation (A.21) is given by Equation (A.19) and (A.22) is given by (A.20)-(A.19).

A.2. Omitted Proofs

A.2.1. Lemma: The trading volume is higher in the hot season:$\lambda^H(1 - F(x^H)) > \lambda^L(1 - F(x^L))$.

We first prove this lemma, which we will use later in our proofs. We show this under the simple case where $\mu = 0$. Let H be the right hand intergal $H(x) \equiv \int_h (1 - F(h))dh$. Given that $\nu^z \equiv \lambda^z(1 - F(x^z)) = -\lambda^z H'(x^z)$,

$$\frac{\partial \nu}{\partial \lambda} = -H' - \frac{\lambda^z H'' \frac{H}{r+\delta}}{1 - \frac{\lambda^z H'}{r+\delta}} = \frac{-H' - \frac{\lambda^z}{r+\delta}(H''H - H'H')}{1 - \frac{\lambda^z H'}{r+\delta}},$$

Given that f is log-concave, according to Bagnoli and Bergstrom (2005), H is also log concave, and thus $(\ln H)'' = \frac{H''H - H'H'}{H^2} < 0$, we have $\frac{\partial \nu}{\partial \lambda} > 0$.

For any $\mu > 0$, since a higher switching rate will make buyers in low (hot) season more (less) picky $\frac{\partial x^L}{\partial \mu} > 0$ and $\frac{\partial x^H}{\partial \mu} < 0$, and as $\mu \to \infty$, these two states are almost identical and thus $x^L \longrightarrow x^H$. Hence, $D(\mu) \equiv \lambda^H(1-F(x^H)) - \lambda^L(1-F(x^L))$ must increase in μ. Given that $D(0) > 0$, $D(\mu) > 0 \, \forall \mu$.

A.2.2. Proof for Proposition 1

To derive $\frac{\partial h^z}{\partial u_R}$, we now apply cramer's rule with Equation (A.21) and (A.22). Let K_j and G_j denote the partial derivaties respect to the jth variable. From Equation A.17 and A.18, we have $\Sigma_1^L(x^L, x^H) = -\left(\frac{1-F(x^L)}{r+\delta+\mu}\right)$, $\Sigma_2^L(x^L, x^H) = \frac{1-F(x^H)}{r+\delta+\mu} - \frac{1-F(x^H)}{r+\delta} = \frac{-\mu\left(1-F(x^H)\right)}{(r+\delta+\mu)(r+\delta)} < 0$, and $\Sigma_2^H = -\left(\frac{1-F(x^H)}{r+\delta}\right)$. Hence, the expression for K_j and G_j yields:

$$K_1 = 1 + \frac{\lambda^L(1-F(x^L))}{r+\delta+\mu} > 0,\ K_2 = \frac{\mu\left(1-F(x^H)\right)}{(r+\delta+\mu)\,(r+\delta)} > 0,\ K_3 = \frac{r+\delta}{r}$$

and

$$\begin{aligned} G_1 &= -\left(\frac{r+\delta+2\mu}{r+\delta+\mu}\right) - \lambda^L\left(\frac{1-F(x^L)}{r+\delta+\mu}\right) < 0,\ G_3 = 0, \\ G_2 &= \left(\frac{r+\delta+2\mu}{r+\delta+\mu}\right) + \lambda\left(\frac{1-F(x^H)}{r+\delta}\right) - \frac{\mu\lambda^L\left(1-F(x^H)\right)}{(r+\delta+\mu)\,(r+\delta)} > 0 \end{aligned}$$

Thus, we have

$$\frac{\partial x^H}{\partial u_R} = \frac{-\left(\frac{r+\delta}{r}\right)G_1}{-(K_1G_2 - K_2G_1)} \propto -\left\{\left(\frac{r+\delta+2\mu}{r+\delta+\mu}\right) + \lambda^L\left(\frac{1-F(x^L)}{r+\delta+\mu}\right)\right\} < 0 \tag{A.23}$$

and

$$\frac{\partial x^L}{\partial u_R} = \underbrace{\frac{-\left(\frac{r+\delta}{r}\right) G_2}{K_1G_2 - K_2G_1}}_{>0} \propto -\left\{\left(\frac{r+\delta+2\mu}{r+\delta+\mu}\right) + \lambda^H\left(\frac{1-F(x^H)}{r+\delta}\right) - \frac{\mu\lambda^L\left(1-F(x^H)\right)}{(r+\delta+\mu)(r+\delta)}\right\} \tag{A.24}$$

$$= \left\{\left(\frac{r+\delta+2\mu}{r+\delta+\mu}\right) + \left(1-F(x^H)\right)\left(\underbrace{\frac{\lambda^H}{r+\delta} - \frac{\mu\lambda^L}{(r+\delta+\mu)(r+\delta)}}_{>0}\right)\right\} > 0.$$

Since DOM decreases with the cutoff, this thus establishes that DOM decreases with rent risk.

A.2.3. Proof for Lemma 1

From Equation (A.23) and (A.24), we have

$$\begin{aligned}
\left(\frac{\partial x^H}{\partial u} - \frac{\partial x^L}{\partial u}\right) &= \frac{1}{(K_1G_2 - K_2G_1)}\left\{\lambda^H\left(\frac{1-F(x^H)}{r+\delta}\right) - \lambda^L\left(\frac{1-F(x^L)}{r+\delta+\mu}\right) - \frac{\mu\lambda^L\left(1-F(x^H)\right)}{(r+\delta+\mu)(r+\delta)}\right\} \\
&\propto \lambda^H\left(\frac{1-F(x^H)}{r+\delta}\right) - \lambda^L\left(\frac{1-F(x^L)}{r+\delta}\right) - \lambda^L\left(\frac{1-F(x^L)}{r+\delta+\mu}\right) \\
&.. + \lambda^L\left(\frac{1-F(x^L)}{r+\delta}\right) - \frac{\mu\lambda^L\left(1-F(x^H)\right)}{(r+\delta+\mu)(r+\delta)} \\
&= \frac{1}{(K_1G_2 - K_2G_1)}\left\{\lambda^H\left(\frac{1-F(x^H)}{r+\delta}\right) - \lambda^L\left(\frac{1-F(x^L)}{r+\delta}\right) + \frac{\mu\lambda^L\left(F(x^H)-F(x^L)\right)}{(r+\delta+\mu)(r+\delta)}\right\} > 0
\end{aligned}$$

The inequality follows from the fact that $\lambda^H(1-F(x^H)) > \lambda^L(1-F(x^L))$, by Lemma A.2.1.

A.2.4. Proof for Proposition 2

For general $\mu \geq 0$, the average price yields: given that $p^z(h) = \beta\Omega^z(h) + J^z$, we have

$$
\begin{aligned}
p^z(h) &= \frac{\beta\left\{h + u_R + \mu\left(\Omega^{z'}(h) - \Omega^z(h)\right) - \lambda^z\Sigma^z\right\}}{r+\delta} + \frac{\beta\lambda^z\Sigma^z + \mu\left(J^{z'} - J\right)}{r} \\
&= \frac{\beta\left\{h + u_R\right\}}{r+\delta} + \frac{\mu\left(\beta(\Omega^{z'}(h) - \Omega^z(h)) + \left(J^{z'} - J^z\right)\right)}{(r+\delta)} + \frac{\delta}{r}\left(\frac{\beta\lambda^z\Sigma^z + \mu\left(J^{z'} - J\right)}{(r+\delta)}\right).
\end{aligned}
$$

Given that Equation (A.16) and $(r + 2\mu)\left(J^{z'} - J^z\right) = \beta(\lambda^{z'}\Sigma^{z'} - \lambda^z\Sigma^z)$, we thus have, for small δ, $p^z(h) \to \frac{\beta\{h+u_R\}}{r+\delta}$ and

$$
P^z = \mathbb{E}[p^z(h)|h \geq x^z] \to \frac{\beta u_R}{r+\delta} + \frac{\beta\mathbb{E}[h|h \geq x^z]}{r+\delta}.
$$

Let $v(x) \equiv \int_{x^z} (h - x^z) \frac{dF(h)}{1-F(x^z)} = \frac{-H(x^z)}{H'(x^z)} = \int_{x^z} \frac{hdF(h)}{1-F(x^z)} - 1$.

$$
\begin{aligned}
\left\{\frac{\partial P^H}{\partial u_R} - \frac{\partial P^L}{\partial u_R}\right\} &\propto \left\{\left(1 + v'(x^H)\right)\frac{\partial x^H}{\partial u_R} - \left(1 + v'(x^L)\right)\frac{\partial x^L}{\partial x_R}\right\} \\
&= \left(1 + v'(x^H)\right)\left(\frac{\partial x^H}{\partial u_R} - \frac{\partial x^L}{\partial x_R}\right) + \left(v'(x^H) - v'(x^L)\right)\frac{\partial x^L}{\partial x_R} > 0
\end{aligned}
$$

Observe that $v'(x) = -\left(\frac{(H')^2 - HH''}{(H')^2}\right) = -(1+q(x))$, where $q(x) \equiv \frac{H}{H'}\left(\frac{H''}{-H'}\right) = \frac{H}{H'}\left(\frac{F'(x)}{1-F}\right) < 0$. Given that f is log concave, we have $\frac{F'(x)}{1-F}$ increases in x and $\frac{H}{H'}$ increases with x, and thus $q'(x) > 0$ and $v''(x) < 0$.

Since $v''(x) < 0$ and $\frac{\partial x^H}{\partial u_R} > \frac{\partial x^L}{\partial u_R}$, we thus have $\frac{\partial P^H}{\partial u_R} > \frac{\partial P^L}{\partial u_R}$.

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Table 1: Summary Statistics

We report summary statistics of variables that we compute from Zillow data from December 2011 to March 2016. Price-to-Rent Ratio is the ratio of home price to rent price using the Zillow home price, expressed as the median home value (psf) in a MSA in a month, and the Zillow rent price, expressed as the median rent value (psf) in a MSA in a month. Days on Market is the median number of days all listings have been current on Zillow. Cross-Sectional Rent Risk is the moving average of the standard deviation of 1 month lagged real rent growth in zip codes within a MSA for past 12 months, using the Zillow rent price (psf). Time-Series Rent Risk is the standard deviation of real rent growth in a MSA in the past 12 months. The standard deviations of real rent growth for zip codes in a MSA using the Zillow rent price are equally weighted within counties and then the county averages are population weighted to the MSA-level. We winsorize all variables at 1% and 99% level by year-month.

Variables	Obs	Mean	Std. Dev.	Min	Max
Days on Market	7678	84.01	25.48	17	166
Price-to-Rent Ratio	11826	10.84	2.38	6.87	21.01
Cross-Sectional Rent Risk	11826	0.64	0.29	0.16	3
Time-Series Rent Risk	11826	0.95	0.43	0.35	4.66

Table 2: Transition Probability

We report year to year transition matrices of rent risks, the Price-to-Rent Ratio and Days on Market. Panel A reports the transition matrix of the Cross-Sectional Rent Risk. In each year, we sort MSAs into quartile groups by their average Cross-Sectional Rent Risk of the year. We then compute the transition probabilities year to year between quartile groups. Panel B reports the transition matrix of the Time-Series Rent Risk. Panel C reports the transition matrix of the Price-to-Rent Ratio. Panel D reports the transition matrix of the Days on Market.

Panel A: Cross-Sectional Rent Risk

Quartile in Year $t-1$ \ Quartile in Year t	1	2	3	4
1	**81.88 %**	14.86 %	2.54 %	0.72 %
2	17.79 %	**54.8 %**	24.56 %	2.85 %
3	2.14 %	27.76 %	**52.31 %**	17.79 %
4	0 %	2.81 %	21.75 %	**75.44 %**

Panel B: Time-Series Rent Risk

Quartile in Year $t-1$ \ Quartile in Year t	1	2	3	4
1	**66.67 %**	26.09 %	6.88 %	0.36 %
2	24.56 %	**47.69 %**	24.56 %	3.2 %
3	9.61 %	24.91 %	**47.69 %**	17.79 %
4	0.35 %	3.51 %	20.35 %	**75.79 %**

Table 2 Continues

Panel C: Price-to-Rent Ratio

Quartile in Year t

Quartile in Year $t-1$	1	2	3	4
1	**86.96 %**	12.32 %	0.72 %	0 %
2	13.52 %	**77.58 %**	8.19 %	0.71 %
3	0 %	9.96 %	**82.96 %**	7.12 %
4	0 %	0 %	7.72 %	**92.28 %**

Panel D: Days on Market

Quartile in Year t

Quartile in Year $t-1$	1	2	3	4
1	**82.78 %**	15.89 %	1.32 %	0 %
2	15.89 %	**62.91 %**	20.53 %	0.66 %
3	2.65 %	19.21 %	**56.95 %**	21.19 %
4	0 %	0.65 %	20 %	**79.35 %**

Table 3: Seasonality of Variables

We report panel regression estimates of the seasonality of our variables of interest. We use MSA-year-month observations from December 2011 to March 2016. The dependent variable in columns (1)-(2) is the Cross-Sectional Rent Risk (1m), the standard deviation of 1 month lagged real rent growth in zip codes within a MSA using the Zillow rent price (psf). Column (1) includes the Hot Season (Broad), which is equal to 1 for April, May, June, July, August and September, and 0 otherwise, MSA fixed effects and Year fixed effects. Column (2) includes the Hot Season (Narrow), which is equal to 1 for May, June, July and August, and 0 otherwise. The dependent variable in columns (3)-(4) is Price-to-Rent Ratio, the ratio of home price to rent price using the Zillow home price, expressed as the median home value (psf) in a MSA in a month, and the Zillow rent price, expressed as the median rent value (psf) in a MSA in a month. The dependent variable in columns (5)-(6) is the Days on Market, the median number of days all listings have been current on Zillow. Regression specifications are same as the columns (1)-(2). The table reports point estimates with t-statistics in parentheses. All the standard errors are clustered at MSA level. ***, **, * denotes 1%, 5%, and 10% statistical significance.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Cross-Sectional Rent Risk (1m)		Price-to-Rent Ratio		Days on Market	
Hot Season (Broad)	-0.001		-0.003		-20.306***	
	(-0.14)		(-0.66)		(-25.88)	
Hot Season (Narrow)		0.0002		-0.003		-17.891***
		(0.02)		(-0.75)		(-23.37)
Observations	11,826	11,826	11,826	11,826	7,678	7,678
R-squared	0.496	0.496	0.931	0.931	0.745	0.700
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: The Effect of Rent Risk on Days on Market

We report panel regression estimates of the effect of Rent Risk on Days on Market. We use MSA by year by month observations from December 2011 to March 2016. The dependent variable is the Days on Market, the median number of days all listings have been current on Zillow. Columns (1)-(4) use the Cross-Sectional Rent Risk. In column (1), the independent variables are the Cross-Sectional Rent Risk with Year-Month fixed effects and MSA fixed effects. In column (2), the independent variables are the Cross-Sectional Rent Risk with Year-Month-Income Quartile fixed effects and MSA fixed effects. We use the MSA total income in 2011 to create the Income Quartiles. In column (3), the independent variables are the Cross-Sectional Rent Risk with Year-Month-Income Quartile fixed effects, Year-Month-Region fixed effects and MSA fixed effects. Region is the Census region where MSA are located. In column (4), the regression specification is the same as in column (1) but we restrict our sample to large MSAs. Large MSAs are the top quartile MSAs by 2011 MSA population. Columns (5)-(8) use the Time-Series Rent Risk. Regression specifications are otherwise the same as in columns (1)-(4). The table reports point estimates with t-statistics in parentheses. All the standard errors are clustered at MSA level. ***, **, * denotes 1%, 5%, and 10% statistical significance.

	Cross-Sectional Rent Risk				Time Series Rent Risk			
	Full Sample			Large MSA	Full Sample			Large MSA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	Days on Market							
Rent Risk	-4.411**	-5.184**	-4.299**	-7.405**	-2.244**	-2.507**	-2.354**	-4.718*
	(-2.04)	(-2.41)	(-1.99)	(-2.10)	(-2.08)	(-2.25)	(-2.03)	(-1.68)
Observations	7,678	7,678	7,678	2,472	7,678	7,678	7,678	2,472
R-squared	0.825	0.832	0.861	0.863	0.825	0.832	0.861	0.863
MSA Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Month Effects	Yes	—	—	Yes	Yes	—	—	Yes
Year × Month × Income Quartile Effects	No	Yes	Yes	No	No	Yes	Yes	No
Year × Month × Region Effects	No	No	Yes	No	No	No	Yes	No

Table 5: The Effect of Rent Risk on Price-to-Rent Ratio

We report panel regression estimates of the effect of Rent Risk on Price-to-Rent Ratio. We use MSA by year by month observations from December 2011 to March 2016. The dependent variable, Price-to-Rent Ratio, is the ratio of home price to rent price using the Zillow home price, expressed as the median home value (psf) in a MSA in a month, and the Zillow rent price, expressed as the median rent value (psf) in a MSA in a month. Columns (1)-(3) use the Cross-Sectional Rent Risk. In column (1), the independent variables are the Cross-Sectional Rent Risk with Year-Month fixed effects and MSA fixed effects. In column (2), the independent variables are the Cross-Sectional Rent Risk and its interaction with the Hot Season (Broad) Indicator, which is equal to 1 for April, May, June, July, August and September, and 0 otherwise. In column (3), independent variables are the Cross-Sectional Rent Risk and its interaction with the Hot Season (Narrow) Indicator, which is equal to 1 for May, June, July and August, and 0 otherwise. Columns (4)-(6) use the Time-Series Rent Risk. Regression specifications are otherwise the same as in columns (1)-(3). The table reports point estimates with t-statistics in parentheses. All the standard errors are clustered at MSA level. ***, **, * denotes 1%, 5%, and 10% statistical significance.

	Cross-Sectional Rent Risk			Time-Series Rent Risk		
		Broad	Narrow		Broad	Narrow
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Price-to-Rent Ratio					
Rent Risk	0.348**	0.294*	0.315*	0.165*	0.114	0.132
	(2.00)	(1.71)	(1.82)	(1.77)	(1.25)	(1.42)
Hot Season × Rent Risk		0.120***	0.113***		0.116***	0.111***
		(3.87)	(3.79)		(4.28)	(4.25)
Observations	11,826	11,826	11,826	11,826	11,826	11,826
R-squared	0.933	0.933	0.933	0.933	0.933	0.933
MSA Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: The Effect of Rent Risk on Price-to-Rent Ratio – Additional Controls

We report panel regression estimates of the effect of Rent Risk on Price-to-Rent Ratio. We use MSA by year by month observations from December 2011 to March 2016. The dependent variable, Price-to-Rent Ratio, is the ratio of home price to rent price using the Zillow home price, expressed as the median home value (psf) in a MSA in a month, and the Zillow rent price, expressed as the median rent value (psf) in a MSA in a month. Columns (1)-(3) use the Cross-Sectional Rent Risk. In column (1), the independent variables are the Cross-Sectional Rent Risk and its interaction with the Hot Season (Broad) Indicator, which is equal to 1 for April, May, June, July, August and September, and 0 otherwise. We include Year-Month-Income Quartile fixed effects and MSA fixed effects, where we use the MSA total income in 2011 to create the Income Quartiles. In column (2), the independent variables are the Cross-Sectional Rent Risk and its interaction with the Hot Season (Broad) Indicator, controlling Year-Month-Income Quartile fixed effects, Year-Month-Region fixed effects and MSA fixed effects. Region is the Census region where MSA are located. In column (3), the regression specification is the same as in column (3) of Table 5 but we restrict our sample to large MSAs. Large MSAs are the top quartile MSAs by 2011 MSA population. Columns (4)-(6) use the Time-Series Rent Risk. Regression specifications are otherwise the same as in columns (1)-(3). The table reports point estimates with t-statistics in parentheses. All the standard errors are clustered at MSA level. ***, **, * denotes 1%, 5%, and 10% statistical significance.

	Cross-Sectional Rent Risk			Time-Series Rent Risk		
	Full Sample		Large MSA	Full Sample		Large MSA
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Price-to-Rent Ratio					
Rent Risk	0.306*	0.470***	0.310	0.118	0.136**	0.042
	(1.71)	(3.85)	(0.88)	(1.29)	(2.13)	(0.12)
Hot Season × Rent Risk	0.119***	0.061**	0.093**	0.122***	0.106***	0.110*
	(3.82)	(2.11)	(2.30)	(4.38)	(4.58)	(1.83)
Observations	11,826	11,826	2,984	11,826	11,826	2,984
R-squared	0.935	0.966	0.962	0.935	0.965	0.962
MSA Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month Effects	—	—	Yes	—	—	Yes
Year × Month × Income Quartile Effects	Yes	Yes	No	Yes	Yes	No
Year × Month × Region Effects	No	Yes	No	No	Yes	No

Figure 1: Monthly Transaction Volume

The figure reports the variation in monthly transaction volume. In Panel A, we report the average monthly home sales data from NAR from 1989 to 2016. NAR Home Sales Data includes single-family existing home sales. The bars show the average number of monthly transactions in each month. In Panel B, we report the average monthly home sales data from Zillow from Jan 2009 to Dec 2015. Zillow Home Sales Data includes all new and existing single-family homes, condominium and co-ops, but excludes non-standard sales such as bank takeovers of foreclosed properties, title transfers after a death or divorce and non arms-length transactions.

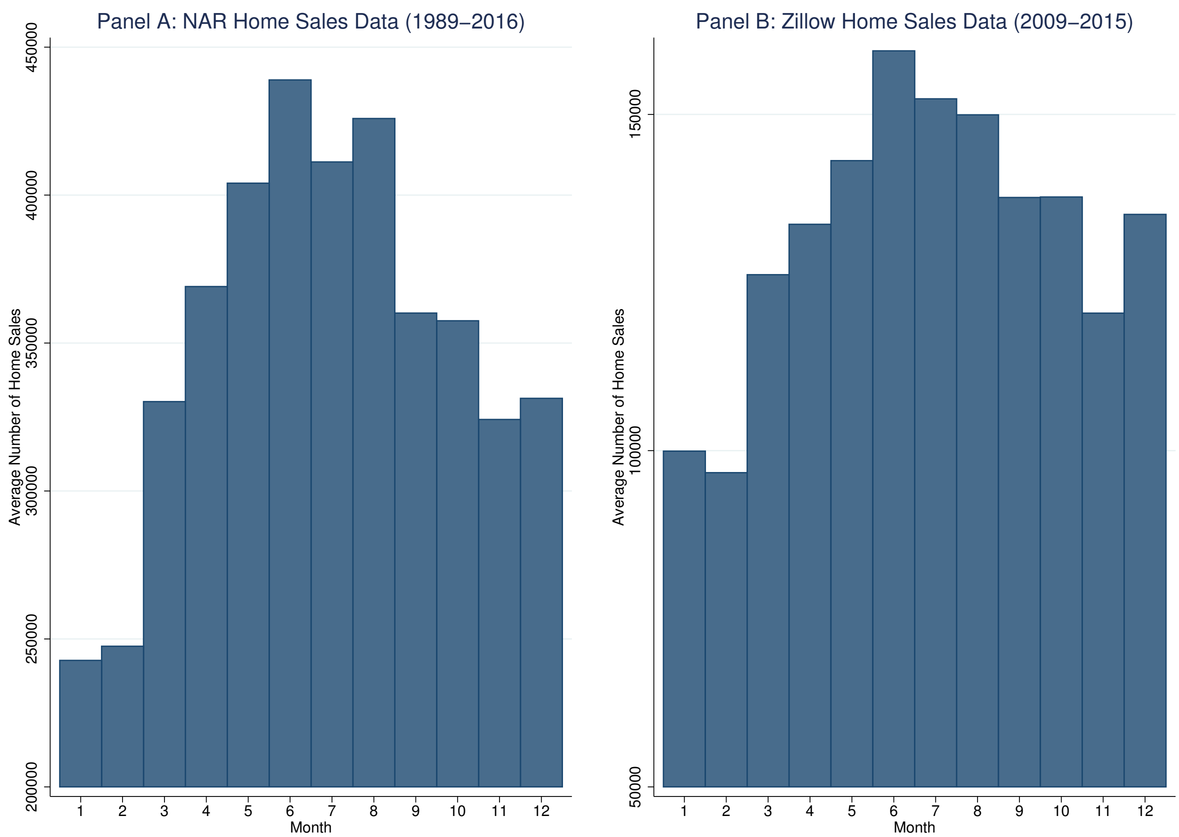

Figure 2: Seasonality

The figure reports the estimates of the seasonality in our variables of interest. Similar to Table 3, we run a regression using our variables of interest as dependent variables and using calendar month dummy as independent variables with MSA fixed effects and Year fixed effects. Panel A reports the coefficients using the Cross-Sectional Rent Risk (1m), the standard deviation of 1 month lagged real rent growth in zip codes within a MSA using the Zillow rent price (psf), Panel B reports the coefficients using the Price-to-Rent Ratio as a dependent variable, and Panel C reports the coefficients using the Days on Market.

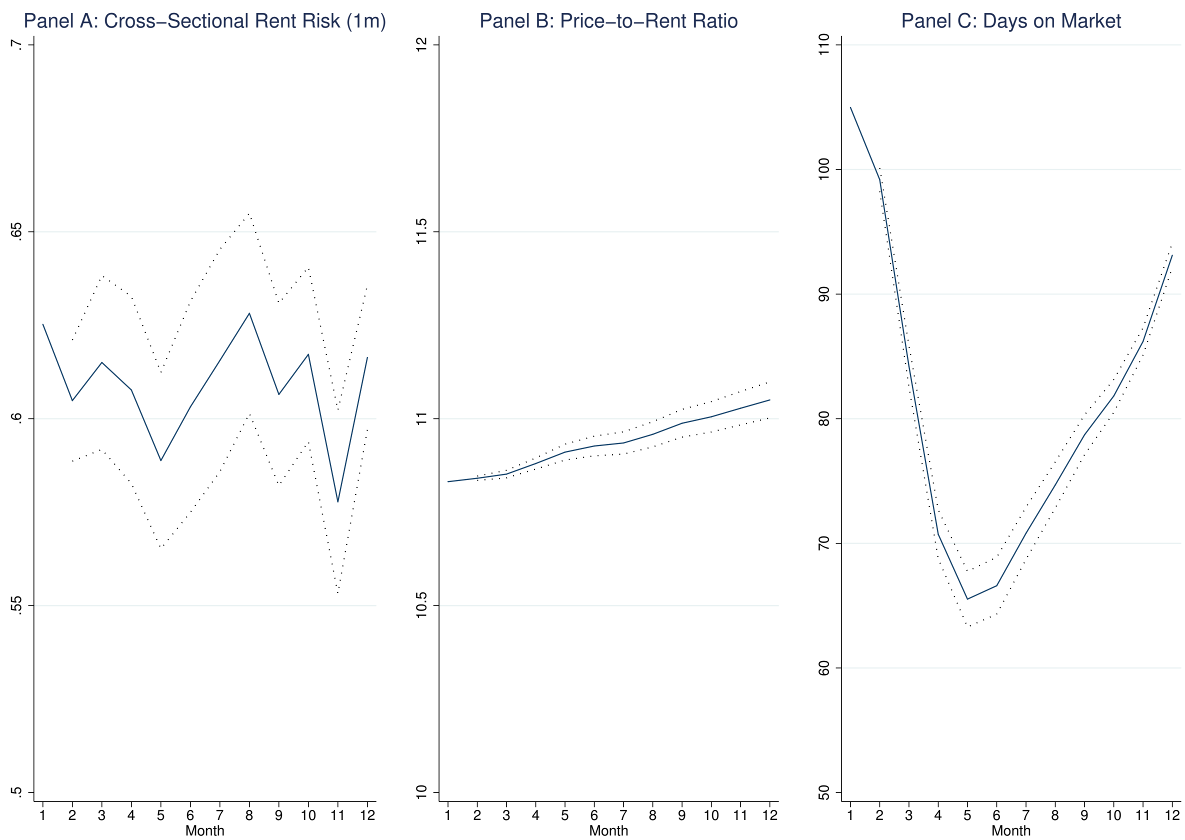

Figure 3: The Coefficients of the Effect of Rent Risk on Price-to-Rent Ratio by Month

The figure reports the estimates of the effect of Rent Risk on Price-to-Rent Ratio by calendar month. Similar to Panel A of Table 5, we run a regression using the Price-to-Rent Ratio as the dependent variable on Rent Risk and its interaction with calendar month dummies as independent variables in addition to MSA fixed effects and Year-Month fixed effects. Panel A reports the coefficients using the Cross-Sectional Rent Risk and Panel B reports the coefficients using the Time-Series Rent Risk. We report 95% confidence interval with dotted lines.