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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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Revisiting supply and demand indexes in real estate*

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Abstract

In this paper we disentangle reservation prices of buyers and sellers for commercial real estate at the city level. To do so, we further develop and extend the Fisher et al. (2003, 2007) methodology to a repeat sales indexing framework. This has the advantage that it takes care of all unobserved heterogeneity, which is an important consideration in commercial real estate. Furthermore, it allows for the construction of supply and demand indexes without the need for many property characteristics or assessed values. A key innovation in our methodology, which also enables granular index production, is our use of a Bayesian, structural time series model for index estimation. By introducing these new methodological developments, we are able to estimate reliable, robust supply and demand indexes for all major metropolitan areas in the US. Here we focus on two very different urban markets: New York and Phoenix. Consistent with the notion of pro-cyclical liquidity, we find that buyers' reservation prices move much more extremely and earlier than sellers' reservation prices. Our results show that the demand indexes in both New York and Phoenix went down a full year earlier than the supply indexes during the crisis.

Keywords: Liquidity, Price index, Commercial real estate.

JEL classifications: R30, C11, C41.

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1. Introduction and Motivation

Two of the most salient characteristics of private property investment markets in comparison with and distinct from public securities markets such as the stock market is the pronounced cyclicity of the private markets and the degree to which their trading volume is pro-cyclical. Price and volume move together in real estate.

This has profound implications for the nature and meaning of asset price indexes in real estate, and these implications are often overlooked. Price indexes are essentially means for comparing the relative differences in prices across time. For example, based on a price index, we might say something like, “values crashed by over 30 percent during the financial crisis.” But what if over the same period trading volume crashed by over 60 percent. Then the “30 percent” drop in the price index does not fully capture the degree to which the asset market collapsed. Nor, by itself does the “60 percent” statistic on trading volume. The observed trading prices that were 30 percent lower than their previous peak as indicated by the price index during the crisis also reflected the fact that property owners chose to sell far fewer properties. The market was much less “liquid” (as this term is used in real estate). The direct comparison of price levels between the peak and trough of the price index is “apples versus oranges” to a large extent.

Fundamentally, observed prices in consummated transactions, the data on which price indexes are based, reflect the reservation prices on the two sides of the asset market, potential buyers on the demand side, and property owners, potential sellers, on the supply side. The volume of trading also reflects these reservation prices. A much deeper and richer, more complete picture of the state of the asset market can be obtained if we can track the central tendencies of these two reservation prices separately over time. The two reservation prices depict more directly the underlying valuation decisions of the two sides of the market. Furthermore, tracking of reservation prices collapses the price and volume dimensions into a single metric. We can make a statement like, “if potential buyers would raise their reservation prices by 20 percent, and sellers would reduce their reservation prices by an equal percent, relative to current average transaction prices, then liquidity as indicated by turnover volume would revert to its long-term historical average.”

In tracking the relative changes over time within buyers’ and sellers’ reservation prices, there is a particularly interesting interpretation of the demand side index, the potential buyers’ reservation prices. The price changes indicated by this index are those which would, in principle, provide the asset market with “constant liquidity” over time. If potential sellers would, in their own reservation prices, match the changes of potential buyers’ reservation prices, then an equal volume of trading (equal turnover ratio) would transpire over time, and this would occur at price changes tracked by the buyers’ reservation price index. Thus, the demand side reservation price index may be taken as a “constant liquidity” price index for the asset market, in some sense a more complete indicator of the state of the asset market, expressed in a single dimension, a price dimension, rather than the two dimensions of price and volume separately.¹

The demand side reservation price index also will provide a leading indicator for where the consummated transaction price index will soon be going. This is because in real estate markets, volume tends to slightly lead consummated transaction prices in time. The reason for this may

¹The contrary model, of buyers’ matching their reservation prices to the sellers’ as though sellers were in “the drivers seat” would not be consistent with the pro-cyclical relationship between price and volume that is so characteristic of the real estate market. See Fisher et al. (2003). From a conceptual perspective, “liquidity” is created by buyers, not sellers. It is buyers who “have the money”, and sellers who “want money”.

be that it is difficult to know the precise implication of relevant “news” for the value of any specific property asset. Market participants can only “digest” the impact of news gradually by observing the prices at which “comparable” properties have traded. Because sellers digest the news slower than buyers, their reservation prices (hence listing prices) tend to lag behind buyers’ reservation prices (Genesove and Han, 2012; Carrillo et al., 2015; Van Dijk and Francke, 2017). The result is that transactions tend to go up (down) when markets go up (down) and that prices go up (down) more gradually. Hence market participants may first gain an indication of the “heat” of the market, the relative movement in supply and demand, by witnessing changes in trading volume, the number of deals that are being completed. Therefore, demand indexes can potentially be used as leading indicators of the real estate market.

The supply side reservation price index will also be of interest in its own right, because it reveals sentiment among property owners. During periods of uncertainty, both rational search theory and behavioral economic theory predict that property owners would tend to react conservatively, holding back from selling into a down market. The supply side index would reveal the extent of this phenomenon.

While it would be nice to have separate indexes of the reservation prices of potential buyers and sellers in the property asset market, these prices are private information, not directly revealed in any single empirical phenomenon. There is probably no single perfect way to track reservation prices. But the fact that both consummated prices and trading volume (turnover ratio) indirectly reflect the underlying reservation prices allows reasonable and useful inferences to be made about the reservation prices. By modeling both price and volume as functions of underlying reservation prices, it is possible to “back out” a reasonable model of the demand and supply side reservation prices, in terms of relative movements or price changes over time, that is, separate price indexes of demand and supply.

The first and most widely employed technique for constructing separate demand and supply reservation price indexes in real estate was pioneered by Fisher et al. (2003, 2007).² Their approach was based on hedonic price modeling of individual sales observations, and it was applied to the NCREIF population of properties (data contributing members of the National Council of Real Estate Investment Fiduciaries). Hedonic price modeling is hampered in commercial real estate applications, because of the scarcity of good data on the relevant hedonic attributes of the properties, which tend to be more heterogeneous than houses. Furthermore, the NCREIF population of properties is rather narrow and specialized, consisting of relatively large, prime properties owned by cash-rich tax-exempt institutions.

In the present paper we further develop and extend the Fisher et al. (2003, 2007) methodology to a repeat sales indexing framework. This enables us to develop demand and supply reservation price indexes for the much larger and broader population of properties represented by the Real Capital Analytics Inc (RCA) database. This database captures approximately 90 percent of all commercial property transactions in the US over \$2,500,000 in value.

The main benefit of using the repeat sales methodology is that it takes care of all unobserved heterogeneity (Bailey et al., 1963), which as noted is a particularly important consideration in commercial real estate. In order to apply the Fisher et al. (2003, 2007) method in a repeat sales framework, we adapt the sample selection methodology for repeat sales models developed by Gatzlaff and Haurin (1997). Perhaps even more importantly, our methodology allows us to esti-

²Goetzmann and Peng (2006) present a slightly different approach that provides similar results. The Fisher et al. (2003, 2007) methodology was employed by the MIT Center for Real Estate to produce and publish a quarterly-updated set of demand and supply indexes during 2006-2011.

mate supply and demand indexes at a much more granular level, in part because it allows us to use the much larger RCA database. The Fisher et al. (2003, 2007) methodology was limited by the NCREIF database coverage to just estimating national indexes, even though property markets are inherently local in nature. A key innovation in our methodology, which also enables granular index production, is our use of a Bayesian, structural time series model for index estimation, building on the work of Francke (2010); Francke et al. (2017). By introducing these new methodological developments, we are able to estimate reliable, robust supply and demand indexes for granular markets. In principle, the method can be applied for every repeat sales data-set with a minimal set or no property characteristics.

In this paper we construct quarterly supply and demand indexes for every major metropolitan area in the United States from 2005Q1–2017Q2. (The index results are available upon request.) Our historical period includes the Global Financial Crisis (GFC), which had not yet occurred at the time when Fisher et al. (2003, 2007) published their work. The GFC is a particularly interesting phenomenon for observing the behavior of the two sides of the market, how the demand collapsed first, while the behavior among property owners was much more conservative and held on to higher reservation prices.

In this paper we focus on the results for the New York City and Phoenix Metro areas (as defined by RCA). These two provide a fascinating “tale of two cities”, as they represent very different underlying urban form and space markets, and displayed interestingly different responses during the Crisis. New York is a typical land supply constrained market with high historical price growth, whereas Phoenix is characterized by sprawl and high supply elasticity in the space market.

Our results show that the demand indexes in both New York and Phoenix went down a full year earlier than the supply indexes during the crisis. In Phoenix, the demand index also went up first after the trough of the crisis. In New York, supply and demand bounced back up together. In New York, the supply index, i.e. property owners’ reservation prices, hardly dropped even during the worst of the crisis, suggesting an impressive confidence in the NYC real estate market on the part of property owners in the face of a financial crisis that hit New York particularly hard. The gap reflected in the relative difference between demand minus supply price movements was much greater in Phoenix than in New York, resulting in a much greater collapse in trading volume (greater loss of liquidity) in the Phoenix market.

The remainder of this paper is organized as follows. Section 2 introduces our methodology. Section 3 gives the data and some descriptive statistics. Section 4 presents the results. Finally, Section 5 concludes.

2. Reservation Prices and Liquidity

First, we discuss the theory of demand and supply in real estate in Section 2.1. Our methodology also follows from this. Section 2.2 gives the estimation procedures.

2.1. Model

The setup of the model is similar to that in Fisher et al. (2003) (henceforth FGGH): Heterogeneous properties are traded among heterogeneous agents in a search market. Both buyers and sellers set their reservation prices based on property characteristics and the market situation:

$$RP_{i,t}^b = \beta_t^b + X_i \alpha^b + \varepsilon_{i,t}^b, \quad (1)$$

$$RP_{i,t}^s = \beta_t^s + X_i \alpha^s + \varepsilon_{i,t}^s. \quad (2)$$

Here RP is the reservation price and subscripts i and t denote the property and time period, respectively. Superscripts b and s represent buyers and sellers. X is a property-specific $1 \times K$ vector of property characteristics and α is the corresponding $K \times 1$ coefficient vector, and $\varepsilon^b, \varepsilon^s$, are independent normally distributed error terms with mean zero. β_t^b and β_t^s are common trends across the reservation prices of all buyers and sellers, respectively. These reflect the market-wide movements of buyers and sellers that we are interested in.

In a search market, we observe a transaction if $RP_{i,t}^b > RP_{i,t}^s$. The distributions of reservation prices of buyers and sellers are displayed in Figure 1. The shaded area is the intersection between the distributions and depicts transaction volume (a larger area reflects more transactions). The outcome of the transaction price $P_{i,t}$ depends on both the sellers' and buyers' bargaining power. We follow Wheaton (1990) and FGGH by assuming that the transaction price is the midpoint between the buyer' and sellers' reservation price.³ The average midpoint price we observe in the market is denoted P_0 in Figure 1. In a booming period the distribution of the reservation price of buyers moves to the right.⁴ This movement results in more transactions and a higher observed average midpoint price, denoted by P_1 . Finally, in a bust buyers move their reservation prices to the left. The intersection area will be smaller which reflects a lower transaction volume and the observed midpoint price will move down to P_2 .

By estimating a normal hedonic regression model we are able to estimate the average midpoint price per time period $\beta_t = \frac{1}{2}(\beta_t^b + \beta_t^s)$, other coefficients $\alpha = \frac{1}{2}(\alpha^b + \alpha^s)$, and residuals $\varepsilon_{i,t} = \frac{1}{2}(\varepsilon_{i,t}^b + \varepsilon_{i,t}^s)$:

$$E(P_{i,t}) = \frac{1}{2}(\beta_t^b + \beta_t^s) + \frac{1}{2}X_i(\alpha^b + \alpha^s) + \frac{1}{2}E((\varepsilon_{i,t}^b + \varepsilon_{i,t}^s)|RP_{i,t}^b \geq RP_{i,t}^s), \quad (3)$$

$$E(P_{i,t}) = \beta_t + X_i \alpha + E(\varepsilon_{i,t}|RP_{i,t}^b \geq RP_{i,t}^s). \quad (4)$$

Let $S_{i,t}^* = RP_{i,t}^b - RP_{i,t}^s$ and substitute Equations (1) and (2) to obtain:

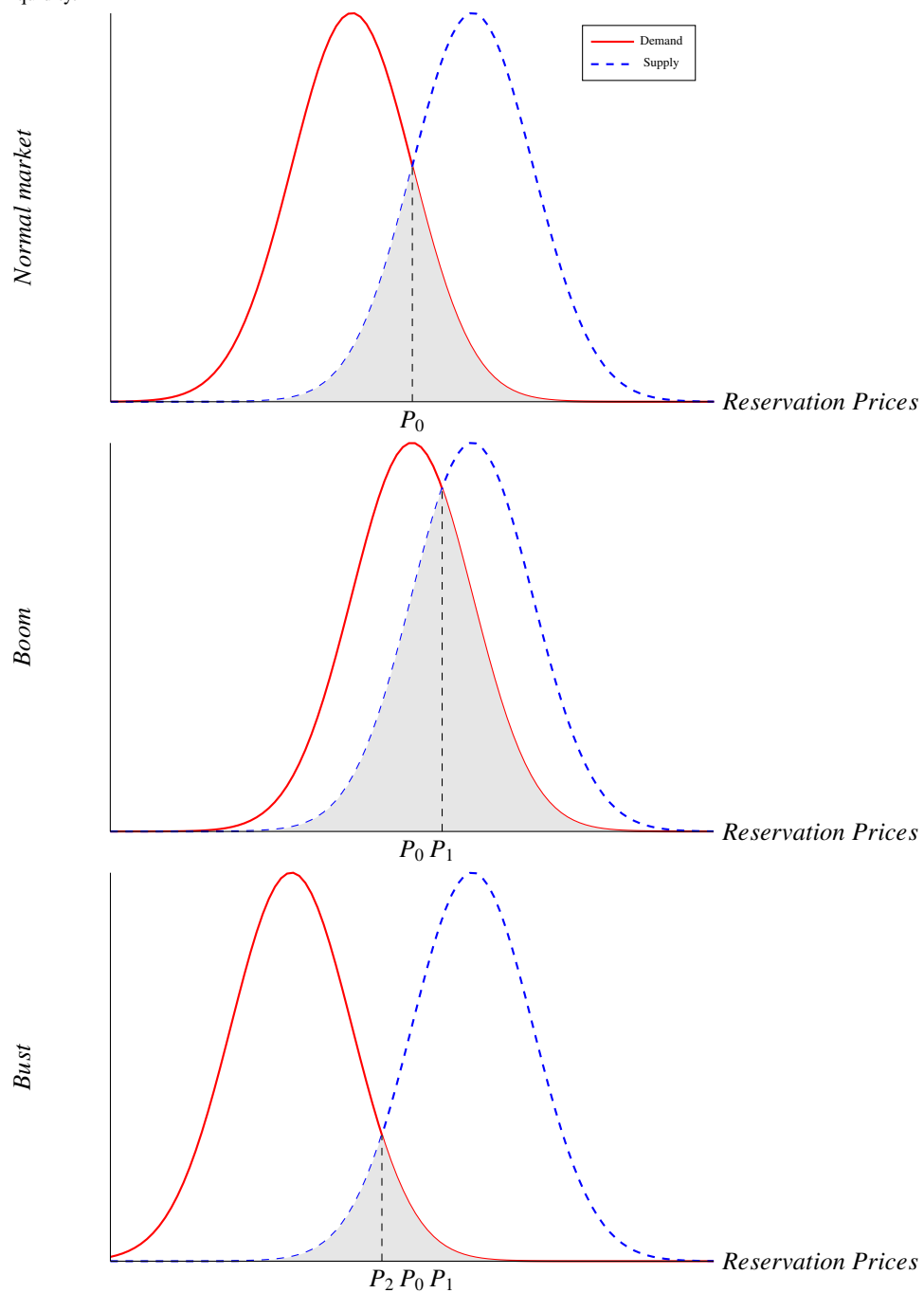
$$S_{i,t}^* = RP_{i,t}^b - RP_{i,t}^s = (\beta_t^b - \beta_t^s) + X_i(\alpha^b - \alpha^s) + (\varepsilon_{i,t}^b - \varepsilon_{i,t}^s). \quad (5)$$

Note that $S_{i,t}^*$ is latent, instead we observe $S_{i,t} = 1$ if a transaction is consummated. Let $\gamma_t = \beta_t^b - \beta_t^s$, $\omega_j = (\alpha^b - \alpha^s)$, and $\eta_{i,t} = \varepsilon_{i,t}^b - \varepsilon_{i,t}^s$. The probability of sale can be estimated by estimating the following probit model:

³We will not pursue the relationship between bargaining power and liquidity here since this would result in difficulties of identification of the reservation prices, see Carrillo (2013) for a discussion on this topic.

⁴The distribution of sellers might also move, but it is generally accepted that buyers respond more quickly than sellers, see Genesove and Han (2012); Carrillo et al. (2015); Van Dijk and Francke (2017). So in our case the buyer reservation prices move *more* to the right than seller reservation prices.

Figure 1: Buyers and seller reservation price distribution at different points in the cycle consistent with pro-cyclical liquidity.



$$S_{i,t}^* = \gamma_t + X_i\omega + \eta_{i,t}, \quad \eta_{i,t} \sim N(0, 1). \quad (6)$$

$$= \Pr(S_{i,t} = 1|X_i) = \Phi(\gamma_t + X_i\omega), \quad (7)$$

here Φ is the cumulative density function (CDF) of the normal distribution. Note that S includes both a subscript i (property) and t (time period): A property is “tracked” over time. $S_{i,t}$ takes the value 1 when the property is sold (once, twice etc.), and 0 when it is not sold in a given period. The γ_t reflects the shift in probability of sale of a given time period. Following FGGH, the inverse Mills ratio (λ_t) is calculated from the probit results. The probit estimation only yields the coefficients up to an estimated scale factor, σ :⁵

$$\hat{\gamma} = \gamma/\sigma = (\beta_t^b - \beta_t^s)/\sigma, \quad (8)$$

$$\hat{\omega} = \omega/\sigma = (\alpha^b - \alpha^s)/\sigma. \quad (9)$$

Deviating from FGGH, we estimate the transaction price model only on repeat sales. This has the advantage that we can take care of all unobserved heterogeneity, which is of importance in the heterogeneous commercial real estate market. This, however, does require some adjustments to the FGGH method. In the next steps, we will discuss these adjustments. We start with the selection corrected repeat sales model of Gatzlaff and Haurin (1997, henceforth GH). The main goal of GH is to correct for the selection bias of second sales versus first sales. The main aim of our set-up is to correct for the bias of sales (either first or multiple) versus no sales. However, with some adjustments we can still apply the GH-model. The two equations for the first and repeat sale conditional on the sale being observed are:

$$E(P_{i,s}|S_{i,s} = 1) = \beta_s + X_i\alpha + E(\varepsilon_{i,s}|S_{i,s} = 1), \quad (10)$$

$$= \beta_s + X_i\alpha + \sigma_{1,3}\lambda_1 + \sigma_{2,3}\lambda_2, \quad (11)$$

$$E(P_{i,t}|S_{i,t} = 1) = \beta_t + X_i\alpha + E(\varepsilon_{i,t}|S_{i,t} = 1), \quad (12)$$

$$= \beta_t + X_i\alpha + \sigma_{1,4}\lambda_1 + \sigma_{2,4}\lambda_2. \quad (13)$$

Here s and t denote the time of first and second sale, respectively. P denotes the (log) transaction price. Note that the equation includes two selection correction variables: λ_1 and λ_2 . These are the inverse Mills ratios for the first and second sale, respectively. In GH these are derived by estimating a bivariate probit on the probability of a single sale on the one hand and the probability (conditional on the first sale) of a repeat sale on the other hand. The σ coefficients are covariances between the errors terms of the selection and sale equations. More specifically, the covariance matrix of the four error terms ($\eta_{i,s}, \eta_{i,t}, \varepsilon_{i,s}, \varepsilon_{i,t}$) is defined as (GH):

⁵The conditions for the identifiability of this “probit σ ” in our context are discussed later on.

$$\Sigma = \begin{pmatrix} 1 & \sigma_{1,2} & \sigma_{1,3} & \sigma_{1,4} \\ \sigma_{1,2} & 1 & \sigma_{2,3} & \sigma_{2,4} \\ \sigma_{1,3} & \sigma_{2,3} & \sigma_{3,3} & \sigma_{3,4} \\ \sigma_{1,4} & \sigma_{2,4} & \sigma_{3,4} & \sigma_{4,4} \end{pmatrix}. \quad (14)$$

Subtracting (11) from (13) and adding disturbance terms results in the repeat sales equation from GH:

$$P_{i,t} - P_{i,s} = \beta_t - \beta_s + (\sigma_{1,4} - \sigma_{1,3})\lambda_1 + (\sigma_{2,4} - \sigma_{2,3})\lambda_2 + v_i. \quad (15)$$

By taking the exponent of β , we get a selection corrected price index. The correlations that appear in Equation 15 are $\sigma_{1,3}$, which is the covariance between the error terms of the first selection equation ($\eta_{i,s}$) and first sale equation ($\varepsilon_{i,s}$), $\sigma_{1,4}$, which is the covariance between the error terms of the first selection equation ($\eta_{i,s}$) and second sale equation ($\varepsilon_{i,t}$), $\sigma_{2,3}$, which is the covariance between the error terms of the second selection equation ($\eta_{i,t}$) and first sale equation ($\varepsilon_{i,s}$), and $\sigma_{2,4}$, which is, the covariance between the error terms of the second selection equation ($\eta_{i,t}$) and second sale equation ($\varepsilon_{i,t}$).

In order to estimate constant-liquidity indexes, it is necessary to include a time trend in the probit (*e.g.* by including time fixed effects in the probit). It is not clear whether this should be included in the probit on first sales, on repeat sales, or on both (the original GH model does not include any time fixed effects). Furthermore, it is not straightforward which λ (of the first or repeat sale) should be used to derive the supply and demand indexes in a later stage (see Equations 23 and 25). Therefore, our proposition is to estimate the following repeat sales equation:

$$P_{i,t} - P_{i,s} = \beta_t - \beta_s + \sigma_{\varepsilon,\eta}(\lambda_2 - \lambda_1) + v_i, \quad v_i \sim N(0, \sigma_v^2). \quad (16)$$

This does impose restrictions on the coefficients on the selection correction variables λ . More specifically, (i) $\sigma_{2,3} = \sigma_{1,4} = 0$ and (ii) $\sigma_{2,4} = \sigma_{1,3} = \sigma_{\varepsilon,\eta}$. (i) implies that there is no correlation between the error terms of the first selection (sale) equation and the second sale (selection) equation. This means that the reason to buy cannot be related to the realized gain or loss in the future. Therefore, it is important to remove properties built for redevelopment from the data. (ii) implies the correlation between the first sale and first selection is equal to the correlation of the second sale and second selection. This means that the decision to buy or sell must be “normal”. For example, if a the second sale was in distress, and the first one is not, this assumption is violated. Therefore, properties sold in distress need to be removed.

In the original GH paper, the selection equations were estimated in a bivariate probit and these assumptions were not necessary. Since the selectivity in a repeat sales model (*i.e.* selection effects of second sales vs single sales) was the main goal of the GH paper, these correlations needed to be explicitly modeled. In our set-up we are merely interested in the selection effect of no sale versus a sale, either a first or multiple. Hence, these assumptions are not too restrictive in our case. Moreover, these assumptions are also implicitly made for observations that are sold more than once when deriving supply and demand indexes in the widely applied hedonic framework of FGGH. Finally, as mentioned, one can account partly for these factors by applying the appropriate data filters.

In order to apply the method in thin markets, the time trend in the repeat sales equation is modeled as a random walk with an additional autoregressive parameter (ρ):

$$\Delta\beta_t = \rho\Delta\beta_{t-1} + \xi_t, \quad \xi_t \sim N(0, \frac{\sigma_\xi^2}{1-\rho^2}). \quad (17)$$

The identifiability of the “probit σ ” for a hedonic framework is discussed in the Appendix of FGGH and will also be briefly discussed here. Let $\sigma_s^2 = \text{Var}(\varepsilon_{i,t}^s)$, $\sigma_b^2 = \text{Var}(\varepsilon_{i,t}^b)$, and $\sigma_{s,b} = \text{Cov}(\varepsilon_{i,t}^s, \varepsilon_{i,t}^b)$. Note that these are the (co)variances of equations (1) and (2). The scale parameter, the “probit σ ”, is equal to $\sigma^2 = \sigma_s^2 + \sigma_b^2 - 2\sigma_{s,b}$, which is what we need to solve for. Following FGGH, our model assumes random matching between buyers and sellers and we can assume $\text{Cov}(\varepsilon_{i,t}^b, \varepsilon_{i,t}^s) = 0$. This simplifies the expression: $\sigma^2 = \sigma_s^2 + \sigma_b^2$. The conditional expected variance of the pricing errors ($\varepsilon_{i,t}^2$) in a hedonic model follows from the known relations for the moments of the truncated bivariate normal distribution (Johnson and Kotz, 1972):

$$E(\varepsilon_{i,t}^2 | S_{i,t} = 1) = \sigma_\varepsilon^2 - \sigma_{\varepsilon,\eta}^2 (\gamma_t + X_i\omega)\lambda_{i,t}, \quad (18)$$

$$\text{where } \sigma_\varepsilon^2 = \text{Var}((\varepsilon_{i,t}^b + \varepsilon_{i,t}^s)/2) = (\sigma_b^2 + \sigma_s^2)/4 = \sigma^2/4. \quad (19)$$

As expectation for the squared errors we plug in the squared residuals of the repeat sales model $\hat{\varepsilon}_{i,t}^2$. Note that FGGH use the sum of squared residuals (SSR) from a *hedonic* model. However, the SSR from a *hedonic* model with pair fixed effects is equivalent to the SSR of our *repeat sales* model.⁶ $\hat{\sigma}_{\varepsilon,\eta}^2$ is the square of the estimated coefficient on the inverse Mills ratio, $\hat{\gamma}_t + X_i\hat{\omega}$ is the linear prediction from the probit model, and $\hat{\lambda}_{i,t}$ is the estimated inverse Mills ratio.⁷ To solve for σ_ε^2 we further plug in the estimates of the probit ($\hat{\gamma}_t, \hat{\omega}$, and $\hat{\lambda}_{i,t}$) and repeat sales estimates ($\hat{\varepsilon}_{i,t}^2$ and $\hat{\sigma}_{\varepsilon,\eta}^2$):

$$\hat{\sigma}_\varepsilon^2 = (1/N) \sum_{i=1}^N [\hat{\varepsilon}_{i,t}^2 + \hat{\sigma}_{\varepsilon,\eta}^2 (\hat{\gamma}_t + X_i\hat{\omega})\hat{\lambda}_{i,t}], \quad (20)$$

$$\hat{\sigma} = 2\hat{\sigma}_\varepsilon. \quad (21)$$

Here N is the number of observations from a *hedonic* model, so in our case that would be the number of repeat sales times 2.⁸ Also note that we stack the repeat sales data: every pair gets two observations (buy and sell). In this case we also use the *level* of the inverse Mills ratio of the first and second sale instead of the difference.

In order to derive the buyers’ and sellers’ reservation price indexes, we combine the probit and repeat sales model results to obtain the demand/supply indexes (FGGH). As estimated values

⁶The SSR and MSE are equivalent, but the *individual* squared errors are different. However, since we are eventually interested in the MSE, we can safely assume $E(\varepsilon_{i,t}^2 | S_{i,t} = 1) = \frac{1}{2}E(\varepsilon_{i,1}^2 | S_{i,t} = 1) + \frac{1}{2}E(\varepsilon_{i,2}^2 | S_{i,t} = 1)$, where 1 is the first sale and 2 is the second sale.

⁷Note that we estimate the coefficient on the difference of the inverse Mills ratio, however the restriction $\sigma_{24} = \sigma_{13} = \sigma_{\varepsilon,\eta}$ implies that the coefficient on the difference ($\sigma_{\varepsilon,\eta}$) is the same as the same as the coefficient on the level of the inverse Mills ratio of the first and second sale.

⁸When a property has more than 2 sales, for example 3 sales, this would result in 4 observations in the hedonic model with 2 pair fixed effects. Hence the second sale enters twice.

we have: $\hat{\gamma} = (\hat{\beta}_t^b - \hat{\beta}_t^s)/\hat{\sigma}$ (from equation 8) and $\hat{\beta}_t = \frac{1}{2}(\hat{\beta}_t^b + \hat{\beta}_t^s)$ (from equation 3) $\rightarrow \hat{\beta}_t^s = 2\hat{\beta}_t - \hat{\beta}_t^b$. Substituting the latter in the former, we get the buyers' reservation price index (constant liquidity index):

$$\hat{\gamma} = (\hat{\beta}_t^b - 2\hat{\beta}_t - \hat{\beta}_t^b)\hat{\sigma}, \quad (22)$$

$$\hat{\beta}_t^b = \hat{\beta}_t + \frac{1}{2}\hat{\sigma}\hat{\gamma}_t. \quad (23)$$

$$(24)$$

Further substitution yields the sellers' reservation price index:

$$\hat{\beta}_t^s = \hat{\beta}_t - \frac{1}{2}\hat{\sigma}\hat{\gamma}_t. \quad (25)$$

2.2. Estimation

We estimate the model in a two-step approach (Heckman, 1979). We first estimate probit Equation (7) by maximum likelihood. We subsequently calculate the inverse Mills ratios of the first and second sales. We then plug in the difference between the inverse Mills ratios in the repeat sales model as given by Equation (16). We estimate the repeat sales model in a Bayesian framework similar to the Commercial Property Price Indexes published by RCA (Francke et al., 2017). The difference is that we use normally distributed errors instead of t-distributed errors in order to use the multivariate normality with the probit. Also, we do not allow the signal and noise to vary over time for the sake of simplicity and consistency with the theory.

As explained in Francke and van de Minne (2017) estimating repeat sales models in a structural time series framework, especially with AR components, is very difficult using the Kalman filter. We therefore estimate the model with Markov Chained Monte Carlo simulations. More specifically, we use the No-U-Turn-Sampler (NUTS) to estimate the indexes (Hoffman and Gelman, 2014; Carpenter et al., 2016). The repeat sales indexes are estimated over 4 parallel chains with different initial values. We use 4,000 iterations per chain of which 2,000 are warm-up iterations that we discard. Hence, the total sample size is 8,000. Following Francke et al. (2017), we use the \hat{R} combined with the effective sample size to determine the convergence of the model. We additionally investigate the Monte Carlo error and the Heidelberger-Welch stationarity and halfwidth statistics (Koehler et al., 2009; Heidelberger and Welch, 1981).

3. Data

We use transaction data from Real Capital Analytics (RCA) to estimate the indexes between 2005Q1 and 2017Q2. RCA has a capture rate of more than 90% of properties larger than \$2,500,000. A high capture rate is fundamentally important for our methodology since the probit results should reflect the probability of sale with respect to the whole population. In order to capture the whole population of properties each property should be sold at least once to be included in the database. We are confident that the high capture rate combined with the fact that RCA has been recording transactions since 2000 makes sure that almost all properties in the investment universe are in our data. Besides, properties that are not in the data after 17 years might

never become part of the investment universe that investors are interested in (*i.e.* properties that trade on a regular basis).

The descriptive statistics for the two metropolitan markets (New York City, NY and Phoenix, AZ) are presented in Table 1. The number of properties is more or less constant in the data, which provides confidence that the capture rate of the data is satisfactory. We are not able to identify whether a property gets demolished. We do observe if a property is bought for the purpose of redevelopment. These properties are removed for the reasons outlined in section 2.1. For the same reasons, properties sold in distress are removed.

In the probit equation we control for property size (in log square feet), property type (Apartment, Hotel, Industrial, Office, Retail, and Other), whether the property is in the Central Business District (CBD), and construction period (< 1920 , $1920 - 1945$, $1946 - 1989$, and ≥ 1990). We also use the construction year to filter out properties that were not yet built. Since multiple properties transact before the construction has been finished, we include the property in the probit data two years before completion. If the model is estimated without property characteristics, this provides comparable results (not shown).

In both New York and Phoenix, the crisis is clearly visible in both the number of sales and average transaction price. In 2009 the number of transactions is about 50% lower compared to 2008 and 70-80% lower compared to 2007. The average property size is more or less equal over the sample. Most properties sold in Phoenix are outside of the CBD, whereas in New York most are within the CBD. Properties in New York are, on average, older than in Phoenix and the average construction year increases somewhat over the sample as newly constructed properties enter the data-set.

Table 1: Descriptive statistics of the two markets over the sample.

Year	Sales	Properties in data	Mean Sale Price in MLN \$	Mean Size in 1000 Sqft	Mean CBD	Mean Year Built
<i>New York City, NY</i>						
2005	1,948	17,867	18.7	35.8	0.73	1941
2006	2,215	17,993	21.5	32.4	0.74	1941
2007	2,248	18,062	23.8	30.2	0.75	1940
2008	1,313	18,127	18.8	28.1	0.71	1942
2009	690	18,174	9.9	25.1	0.72	1942
2010	852	18,227	18.3	34.1	0.73	1943
2011	1,090	18,265	23.9	30.9	0.75	1944
2012	1,790	18,298	18.9	24.8	0.83	1938
2013	2,218	18,334	22.1	25.1	0.78	1942
2014	2,423	18,358	24.2	25.7	0.79	1941
2015	2,715	18,366	25.0	23.4	0.77	1942
2016	2,253	18,370	27.0	25.3	0.74	1944
2017*	951	18,371	20.2	23.7	0.67	1946
<i>Phoenix, AZ</i>						
2005	884	4,548	11.5	61.2	0.01	1987
2006	801	4,720	12.6	57.4	0.01	1989
2007	696	4,777	13.6	53.1	0.03	1990
2008	288	4,794	10.4	41.3	0.01	1990
2009	130	4,801	9.1	51.0	0.02	1993
2010	166	4,823	10.4	54.7	0.00	1993
2011	255	4,847	12.3	70.3	0.01	1992
2012	433	4,876	11.6	66.8	0.02	1991
2013	449	4,908	10.9	58.5	0.00	1992
2014	610	4,942	11.3	54.9	0.03	1991
2015	708	4,948	13.4	55.1	0.02	1991
2016	725	4,948	13.6	53.7	0.02	1991
2017*	317	4,948	12.3	52.8	0.03	1990

*2017 only consists of data on the first two quarters.

4. Results

As noted before, our estimation procedure consists of multiple steps. First, we estimate the probability of sale by equation (7) and calculate the inverse Mills ratio. Second, we estimate a repeat sales model including the difference in the inverse Mills ratio by estimating equation (16). Finally, we derive the supply and demand reservation price indexes by combining the probit and repeat sales results using equations (23) and (25).

4.1. Probability of sale

The estimates for the probability of sale for the two markets are shown in Table 2. The estimates of the time fixed effects (γ_t in equation 7) are included in Figure 2. The magnitude of

the coefficients cannot be interpreted directly, but the sign can be interpreted. Furthermore, the relative effects of the categorical variables can be interpreted.⁹

In general, larger properties have a somewhat higher probability of sale, although the effect is only marginally significant. In New York, properties located in the CBD sell quicker. With respect to property types, apartments sell the quickest in both markets and “other” (*i.e.* elderly homes, nursing cares, parking facilities etc.) sell the slowest. Hotel, industrial and office buildings sell roughly at the same speed. The newest buildings (built after 1990) sell the quickest in both markets.

The estimates of the time fixed effects are somewhat noisy (Figure 2). Also, the estimates show a seasonal pattern. Therefore we follow Fisher et al. (2007) and smooth and seasonally adjust these coefficients. More specifically, we use a local linear trend model with a seasonal factor to distinguish between signal and noise. The probability of sale in New York is approximately 50% lower mid 2009 compared the end of 2007 and has recovered gradually to the pre-crisis level between 2010 and 2015. Since 2015, the probability of sale seems to be somewhat decreasing.

The probability of sale in Phoenix decreased by more than 80% during the crisis. The probability of sale increased between 2010 and 2016, but has never recovered fully to the pre-crisis level. Also, starting in 2016 there is a small decrease in the probability of sale in Phoenix. Finally, notice the very similar development in the rate of sales across the two markets. This indicates that there are small differences in regional dynamics in the probability of sale.¹⁰ The development of the probability of sale actually shows a very similar pattern across different markets in the US (not shown in here, but available upon request). This does, however, not imply that the probability of sale is similar across different markets. The baseline level of sales, for example, could be substantially different.

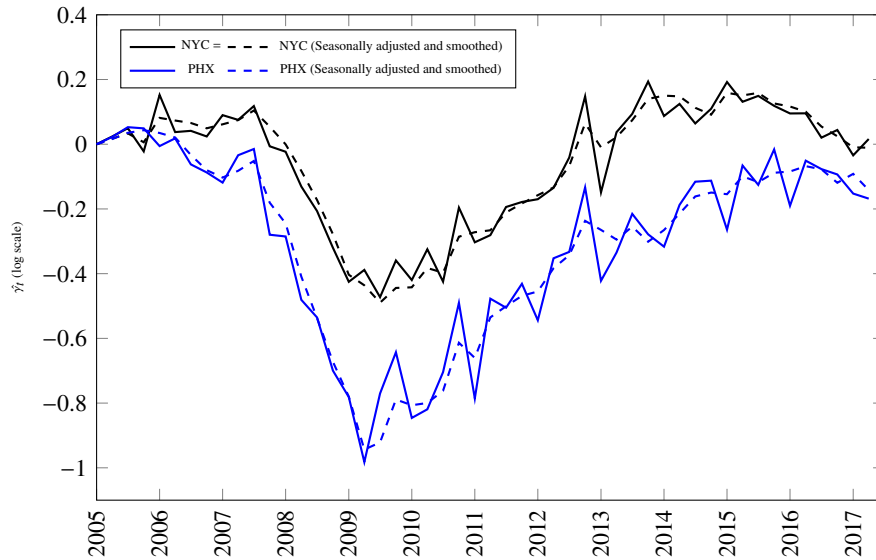
⁹Another option would be to present marginal effects. The supply and demand indexes, however, require the “raw” coefficients. Therefore, we choose to present the coefficients instead.

¹⁰The correlation between the probability of sale in New York and Phoenix is 0.92 in (index)levels and 0.66 in first differences.

Table 2: Coefficient estimates including 95% confidence intervals of the probit equation for the two markets over 2005Q1 and 2017Q2.

Variable	New York City, NY			Phoenix, AZ		
	ω	P2.5	P97.5	ω	P2.5	P97.5
Constant	-1.971	-2.039	-1.903	-1.858	-2.227	-1.488
Log(Size)	0.004	-0.001	0.009	0.006	-0.004	0.017
CBD	0.036	0.020	0.052	0.022	-0.063	0.107
Apartment	(Omitted)			(Omitted)		
Hotel	-0.025	-0.077	0.027	-0.041	-0.105	0.024
Industrial	-0.075	-0.093	-0.057	-0.082	-0.115	-0.050
Office	-0.057	-0.074	-0.041	-0.072	-0.105	-0.039
Retail	-0.055	-0.071	-0.039	-0.083	-0.118	-0.049
Other	-0.079	-0.127	-0.032	-0.145	-0.210	-0.079
Built <1920	(Omitted)			(Omitted)		
Built 1920-1945	0.001	-0.014	0.016	0.137	-0.233	0.507
Built 1946-1989	-0.009	-0.027	0.010	0.145	-0.198	0.489
Built \geq 1990	0.035	0.013	0.057	0.168	-0.175	0.512
Time fixed effects	Yes (γ_t)			Yes (γ_t)		
N	922450			244607		
Loglike	-104607.6			-28847.5		

Figure 2: Raw and smoothed/seasonally adjusted estimates of the time fixed effects in the probit equation (γ_t) for the two markets over 2005Q1 and 2017Q2.



4.2. Repeat sales indexes

The repeat sales indexes for New York and Phoenix are shown in Figure 3. These are the “midpoint-indexes” that follow from the estimation of equation (16). The indexes are, by construction, on the midpoint between the demand and supply indexes. The GFC is clearly visible in

the indexes. New York started recovering in 2010 and the prices surpassed the pre-crisis level in 2013. In contrast, Phoenix has been recovering much more slowly, starting in 2011. Substantial recovery in Phoenix took off not before 2016 when prices increased by almost 25%. The price levels, however, are still lower than the pre-crisis ones at the end of the sample.

The model statistics and the estimate on the coefficient of the difference of the inverse Mills ratio are presented in Table 3. All model statistics are satisfactory, the Monte Carlo error (MC error) is very close to 0 and the effective sample size (Neff) relative to the number of samples is close to 1 for all models (note that the number of samples is 8,000 for every model). The Heidelberger stationary statistic is equal to 1, indicating that the test is passed by every parameter in the model (a parameter gets the value 1 if the test is passed). The same holds for the Heidelberger halfwidth statistic, which is close to 1. This indicates the number of chains is high enough. Finally, the \hat{R} values close to 1 indicate that the models have converged well.

Figure 3: Repeat sales indexes of commercial real estate in New York and Phoenix between 2005Q1 and 2017Q2.

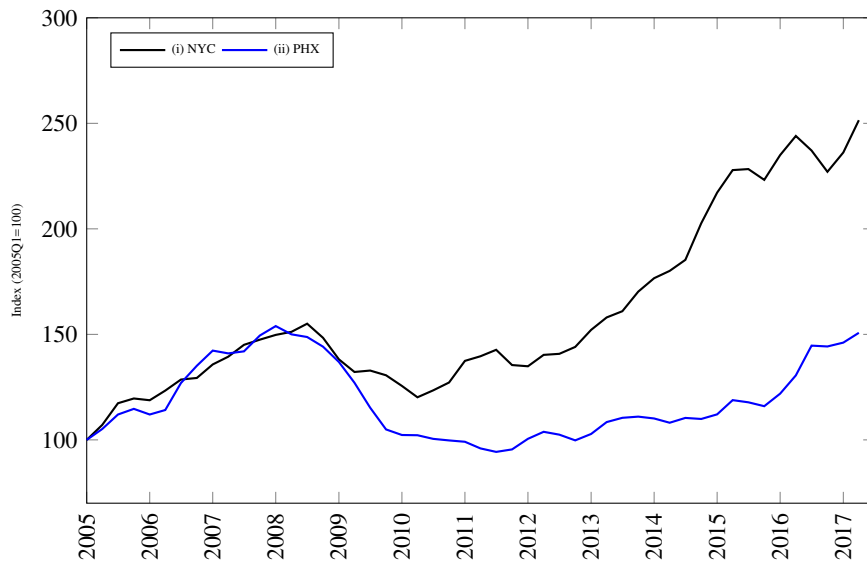


Table 3: Coefficient estimates on the inverse Mills ratio ($\sigma_{\epsilon,\eta}$) in the repeat sales equations including the 95% Highest Posterior Density (HPD) intervals and model statistics.

Statistic	<i>New York City, NY</i>	<i>Phoenix, AZ</i>
$\sigma_{\epsilon,\eta}$	-0.1617	-0.3095
$\sigma_{\epsilon,\eta,p2.5}$	-0.3843	-0.5533
$\sigma_{\epsilon,\eta,p97.5}$	0.0549	-0.0735
Repeat sales	4106	1452
Loglike	-2394.1	-777.2
MC-error	0.0011	0.0024
Neff	7986	7993
Heidelberg stationarity	1.0000	1.0000
Heidelberg halfwidth	0.9889	0.9783
\hat{R}	1.0000	0.9999

Repeat sales denotes the number of repeat sales pairs, Loglike the log-likelihood, MC-error the mean of Monte Carlo standard error for all parameters, Neff the mean effective sample size (total number of samples = 8000) of all parameters, Heidelberg-Welch stationarity and the Heidelberg halfwidth tests are the mean of the tests of all parameters (a parameter gets the value 1 (0) when the test is passed (failed) at the 5% level). Finally, \hat{R} is the mean Rhat statistic for all paramers.

4.3. Supply and demand indexes

The indexes for demand and supply reservation prices that follow from equations (23) and (25) are shown in Figures 4 and 5 (mind the difference in scale). Following Fisher et al. (2007), the indexes are presented such that the mean of the supply and demand indexes are equal. The indexes can also be used as a liquidity indicator; if the difference between demand and supply becomes smaller (larger) there is less (more) liquidity in the market.

In both markets, the demand-side (or constant-liquidity) indexes seem to move quicker and more extreme than the supply side indexes. The demand side indexes are decreasing a year before the supply side indexes during the crisis. Especially in Phoenix, the recovery also happens much earlier. Comparing the demand side indexes from Figure 4–5 and the midpoint indexes from Figure 3, we observe that the demand side constant-liquidity indexes also lead the midpoint indexes. The lead is smaller than the full year in the supply and demand indexes, but it is still visible. A Granger causality analysis confirms this: Changes in the demand side indexes Granger cause changes in the midpoint indexes in both markets. The same holds for the relationship between the demand side and supply side indexes: Changes in supply reservation prices are Granger caused by changes in demand reservation prices at the 1% level.¹¹

In New York, suppliers' reservation prices remained surprisingly constant which suggests that property owners remained very confident about the New York commercial real estate market. The difference between peak (2008Q3) and through (2010Q2) was only 17%, compared to 29% in the demand side index (2007Q3–2010Q2). After the crisis, supply and demand show a joint recovery in New York. In Phoenix, suppliers' reservation remained sluggish through as late as 2015Q4. The difference between peak and through is also much larger in Phoenix: Sellers'

¹¹Both Granger causality analyses are significant at the 1% level and are based on a VAR model with 4 lags estimated separately for each market.

reservation prices went down by more than 40% (2008Q4–2012Q4) and buyers’ reservation went down by 46% (2008Q1–2010Q2).

The more extreme movements of the demand side indexes is also documented in Fisher et al. (2007) and is consistent with the notion of pro-cyclical liquidity. Liquidity, as indicated by the difference between demand and supply reservation prices, substantially decreased during the GFC. This is also clearly visible in the probability of sale (Figure 2).

Figure 4: Supply and demand indexes in the New York City, NY.

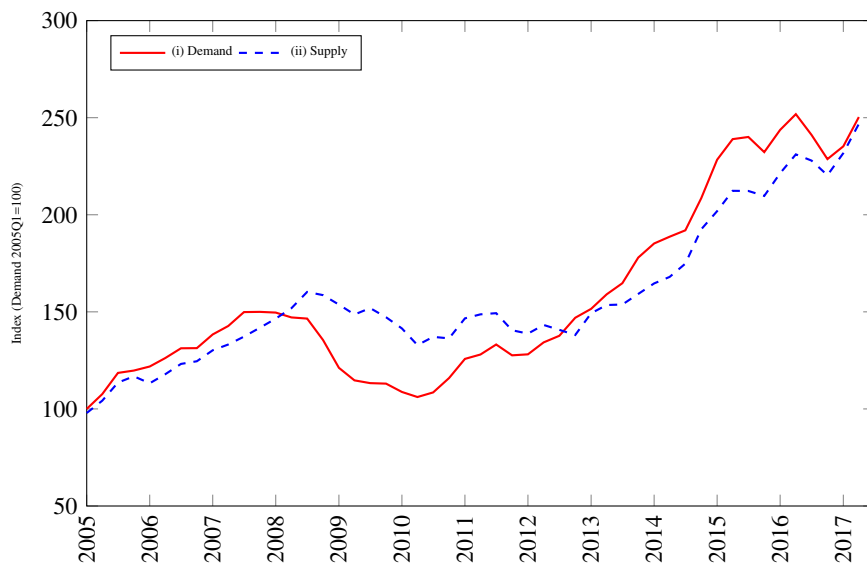
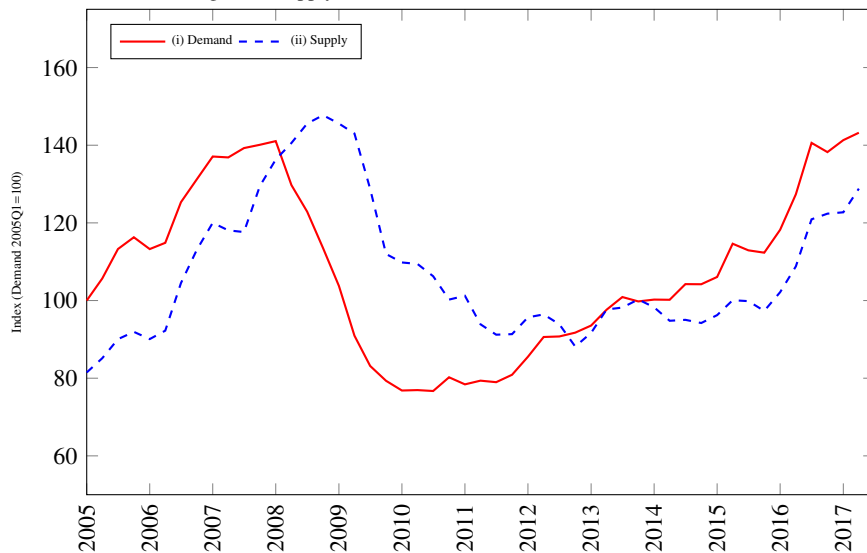


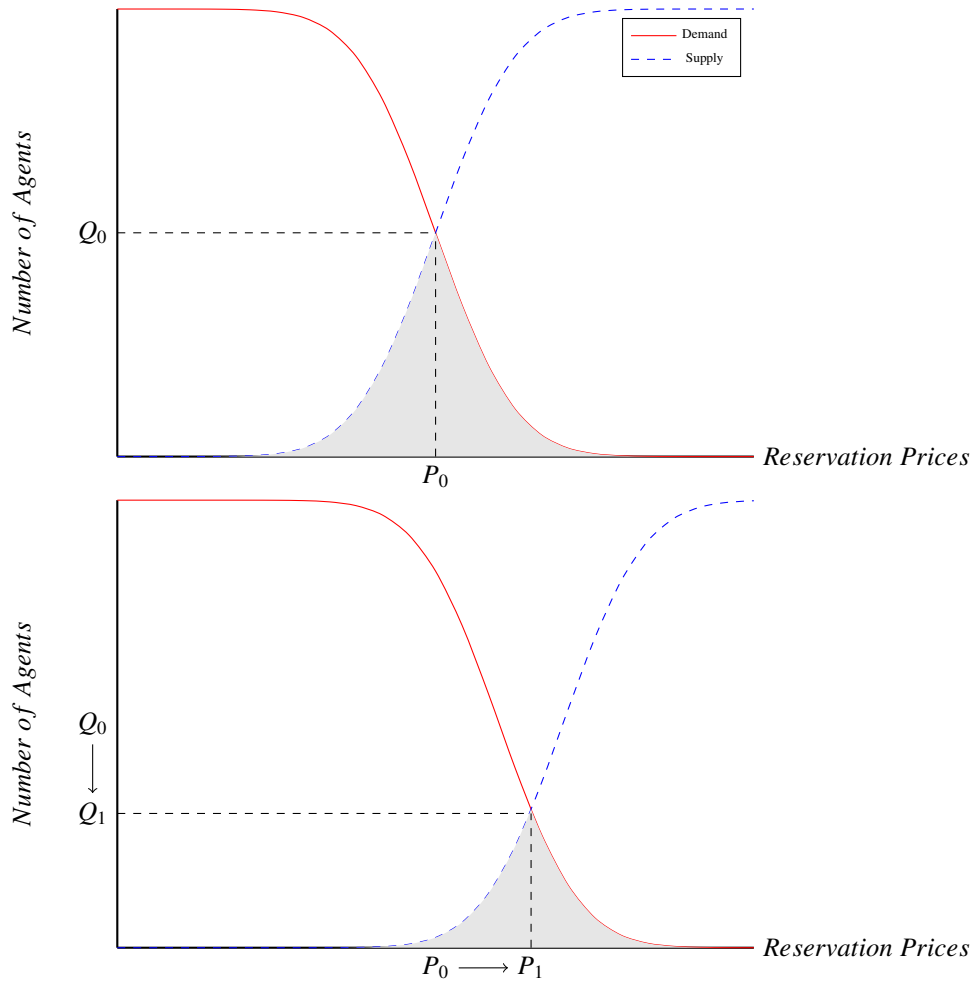
Figure 5: Supply and demand indexes in the Phoenix, AZ.



4.4. A recent anomaly?

Recently, a rare phenomenon is visible in the commercial real estate markets, as prices keep steady or increase, deal volume is going down. Usually, liquidity is pro-cyclical, liquidity goes up when prices go up and vice versa. RCA suggests that a difference in buyer and seller reservation prices is the cause: “The current impasse suggests a widening gap between buyer and seller pricing expectations” (Real Capital Analytics, 2017). This implies that the distribution of sellers’ reservation prices moves more to the right than the distribution of buyers’ reservation prices. This results in fewer transactions and a decrease in liquidity. Prices, however, increase. This is shown in Figure 6, which depicts the cumulative distributions in the reservation prices. Our empirical findings for both Phoenix and New York are consistent with this view. The decrease in liquidity is visible in Figure 2 and the increase in (midpoint) prices is visible in Figure 3. These dynamics are also visible in the supply and demand indexes, especially in New York, where the reservation prices of sellers are increasing more than the reservation prices of buyers in the final year (Figure 4).

Figure 6: Situation where the sellers' distribution of reservation prices shifts more to the right than the buyers' distribution of reservation prices, the cumulative distributions are shown.



5. Conclusions

In this paper we extend the constant liquidity index methodology introduced by Fisher et al. (2003). We introduce two new components: (i) We cast the method in a repeat sales framework, and (ii) we estimate the model in a structural time series format. As a result, we can disentangle reservation prices of buyers and sellers for commercial real estate at a city level without needing a substantial set of property characteristics. We apply our model using data provided by Real Capital Analytics (RCA). RCA tracks properties over \$2,500,000, or the typical institutional / large private investor space. In this paper we focus on two cities in a very different urban setting: New York and Phoenix.

Tracking demand and supply separately does not only give us more insight into the real estate market, it can also be used as a predictive model. Indeed, supply tends to move slower compared to demand, due to anchoring and loss aversion (Bokhari and Geltner, 2011) and issues

related to mortgage debt (Genesove and Mayer, 2001). The “midpoint” index that is usually estimated in a repeat sales framework also lags behind reservation prices of buyers. We find that in both New York and Phoenix demand dropped a full year prior to supply during the crisis. We further find that buyers’ reservation prices went down by 29% and 46% in New York and Phoenix, respectively. In New York, reservation prices of sellers only dropped moderately by 17% compared to the large drop in Phoenix of 40%.

Finally, we document a rare phenomenon. In all markets and for most of the time liquidity is pro-cyclical. In recent quarters, however, prices seem to be increasing and liquidity is decreasing. This is also visible in our demand and supply indexes: Reservation prices of sellers are increasing more than reservation prices of buyers.

Although we only analyzed the indexes for New York and Phoenix, indexes for all major metropolitan areas are available upon request. We encourage future research to examine more markets in different urban settings and to answer additional questions related to reservation price dynamics. Also, our method is general and can be applied to every data set in which repeat sales can be identified and for which transaction prices are known.

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