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Abstract: *Despite their large size and relevance to the overall economy, commercial real estate markets have largely evaded the push for a Big Data revolution. Infrequent transactions and non-disclosure of deal and pricing information are the most commonly named data problems which are particularly pronounced in emerging markets where market monitoring and transaction recording systems are not well established and the institutional market segment may be thin. Beijing is a good example for this situation. A reliable quarterly office rental price index is non-existent. This paper presents a viable approach for estimating a robust and reliable quarterly transaction-based price index based on primary data from the Beijing office market, using a two-stage frequency conversion approach. This new index complements existing valuation-based indices by providing more accurate and timely measurements of market turning points.*

Keywords: emerging office markets, transaction-based index; Chinese cities

JEL classifications: C43, E32, R33

1. Introduction

Real estate as an asset class attracts substantial attention from both institutional and individual investors. Investment managers include real estate into their portfolios to achieve diversification and superior risk-adjusted returns. Therefore, the demand for high quality and accurate real estate indices has emerged to reflect the performance of real estate and the state of the market. Higher-frequency indices (quarterly and monthly) generally provide more up-to-date information, but often with more noise, than low frequency indices (annual). The increase in reporting frequency raises the usefulness of an index enabling more accurate and more in-depth analyses which may in turn lead to better investment decisions and better timing of these decisions. On the other hand, the greater the reporting frequency, the lower the statistical quality per period of index returns as the noise level increases with reporting frequency. Therefore, there is a trade-off between index frequency and noise level (Geltner and Ling, 2006). Recently, the construction of higher-frequency indices has gained particular attention. Bokhari and Geltner (2012) argue that there is an increased demand for reliable higher-frequency indices from the derivatives trading sector. Moreover, higher-frequency indices provide greater opportunity to perform a sophisticated econometric analysis of the real estate market due to the large sample size. This is particularly important for emerging markets, such as Beijing, as these markets generally have a relative short development history.

Asset allocation and portfolio theories show that the inclusion of real estate investments in traditional equity and bond portfolios can provide diversification benefits. More importantly, the inclusion of real estate investments from emerging markets may potentially lead to even greater diversification low correlation with developed market asset returns. China is a major developing market that is undergoing a transition from a pure planned economy to a free market economy. The existence of state-owned enterprises (SOEs), a managed floating exchange rate regime, a consistent trade surplus, significant GDP growth and frequent government interventions distinguish China from most developed markets. The sheer size and distinct structural features have arguably made China's economy resilient to past market shocks emanating from developed markets. If this pattern can be sustained, Chinese real estate investments may offer low or even negative correlations, higher risk-adjusted returns and diversification benefits to global investors. Beijing, the capital city of China, experienced large foreign direct investment flows in past decades. In addition, many foreign enterprises entered the Chinese market by establishing offices in Beijing. According to CBRE Global Research's database, 76% of modern office tenants in Beijing's CBD are either foreign enterprises or joint ventures. As Wang, et al (2011) demonstrates for Chinese urban areas, their varying degrees of openness are a significant determinant of real estate prices in each of these cities. In this vein, market transparency and the availability of timely and accurate real estate price indices are not only important for real estate investors and enterprises to understand and evaluate market dynamics but may also contribute more broadly to the development of urban property markets in China.

This paper seeks to fill the existing gap by investigating and implementing a suitable method for constructing a quarterly rental index for the Beijing office market. The rest of this paper is organized in the following manner. The next section presents a review of the relevant literature on the construction of real estate price indices. Section 3 explains the data and methodology. Section 4 describes the empirical results of the index construction and provides a comparison with an index constructed by a real estate service provider. Finally, we discuss the conclusion and implications in Section 5.

2 Current state of research

The most crucial decision for establishing a real estate index is to nature of the underlying individual transactions. The principal building blocks of a real estate index are valuations, transaction prices or a mix thereof (hybrid). All three types have characteristics that make them suitable for specific purposes but they also have drawbacks that need to be addressed or at least be made transparent when establishing an index in an emerging market. This section offers a review of the existing three approaches.

Valuation-based index

A valuation-based index measures the movement of office rents and prices through repeated valuations. The index is constructed by valuing a group of office buildings on a regular basis. The value of the group of office buildings at different time intervals constitutes a valuation based index. The valuation-based index is very popular in commercial real estate markets, because it overcomes the low transaction volume and sample selection bias caused by the illiquid and non-transparent nature of this market through estimation of current market value instead of using real transactions.

The main weaknesses of valuation-based indices include: random noise and the temporal lag bias (Geltner 1993a, Geltner 1993b, Fisher, Geltner and Webb 1994, Geltner and Fisher 2007). There appears to be a trade-off between random error and the temporal lag bias. Increasing the total number of observations will improve estimation accuracy by reducing the random error but as time periods are extended and more observations are gathered a temporal lag bias arises. Therefore, it is impossible to eliminate both errors simultaneously. In addition, Geltner (1993a) argues that even if appraisers use only current transaction values, the valuation smoothing bias would still occur due to the temporal aggregation bias of combining the transaction values of different points in time in a given period into a single index value for that period. Furthermore, Lai and Wang (1998) find that valuation smoothing might also be due to the cognitive behaviour of appraisers. For example, appraisers might face pressure from managers to report a rate of return that meets the latter group's target rates. Finally, appraisers might also encounter measurement error in revaluing the property because the valuation process is to some degree subject to individual judgement. The consequence of both random error and temporal lag bias puts the reliability of a valuation-based index into question. This may be problematic for real estate investment activities such as multi-asset allocation and risk and return comparisons across asset classes.

The IPD total return index and NCREIF Property Index (NPI) are two popular valuation-based indices in the US and the UK. Lee, Lizieri and Ward (2000) found that the IPD and Richard Ellis valuation-based indices exhibited lower volatility compared to market-traded equities. There is statistical significant evidence of a strong serial correlation in these indices. These indicated the existence of potential valuation smoothing and lag bias. Moreover, Fisher, et al (1994) found that the low volatility of valuation-based indices causes indices to miss market turning points particularly when the onset is sudden. For example, the Russell-NCREIF (RN) valuation-based index failed to register the rapid declines in commercial property values in the late 1980s at a time when many financial institutions were being declared insolvent. In order to overcome the potential bias in the valuation-based index, index de-smoothing and reverse-engineering have been developed (Fisher, et al 1994, Geltner and Miller 2001 and Fu (2003).

The aim of valuation desmoothing is to reverse-engineer the appraisal process to obtain the index returns without a lagged representation of the true market index. The early research on this topic makes relatively strong assumptions about the smoothing model and procedures. One approach assumes that the underlying unobserved true market returns are unpredictable and uncorrelated across time (Geltner 1989, Ross and Zisler 1991, Quan and Quigley 1991 and Gyourko and Keim

1992). However, Geltner (1993b) present an approach to desmoothing the valuation-based index without assuming complete market efficiency. Schwann (1998) proposes a hedonic index that is based on a Kalman filter and stationary autoregressive process. More recently, Lizieri, Satchell and Wongwachara (2012) developed a regime-switching threshold autoregressive model to desmooth the valuation-based index based on both a return- generating process and appraiser behaviour. The authors find that this approach yields superior results compared to earlier desmoothing models.

Transaction-based index

A transaction-based index can potentially overcome the problem of valuation smoothing by using real transactions instead of valuations as it offers more timely information than the valuation-based index, especially for market turning points (Fisher, et al, 2007, Geltner and Fisher, 2007, Chegut, Eichholtz and Rodrigues, 2013). However, the transaction-based index is not without problems itself. Although the construction of a transaction-based index avoids the valuation smoothing bias that might be encountered in valuation based index, the scarcity of transaction data creates a noise problem in the estimate of transaction based index. The problem is more severe in the office market, because transactions are less frequent than in the residential market. Geltner and Ling (2006) classified the error types into pure noise error, valuation smoothing error and total error. They argued that the valuation-based index is superior in the pure noise dimension whereas the transaction-based index is superior in both the valuation smoothing and the total error dimension. Therefore the transaction-based index is superior to the valuation-based index when the research objective is to minimise the overall index error. Transaction-based indices are useful for emerging markets, especially for the Beijing office market. Emerging markets generally have low transparency and low liquidity which affect the accuracy of property and rental valuations. Transaction-based indices used real transaction which can provide useful information about the movement of office markets in emerging markets.

Hedonic pricing and repeated sales indices are the two most common transaction-based approaches.

Hedonic approach

Lancaster (1966) provided the microeconomic foundations for investigating the attributes of goods. Rosen (1974)'s seminal theory of heterogeneous goods was the origin of the hedonic pricing model. The hedonic pricing approach captures the heterogeneous nature of real estate by regressing the real estate price to its determinants. It effectively decomposes the real estate price into various important components. Researchers often pool all the data together and estimate a single hedonic regression with inclusion of the time dummy variables. The estimated coefficients of time dummy variables yield the real estate price indices. Fisher, et al (2007) constructed a quarterly transaction based index by using a hedonic pricing approach for property level investment performance for US institutional real estate investors. They argued that the hedonic pricing transaction-based index can avoid the potential valuation smoothing and lag bias encountered in NPI in the US.

The standard log linear functional form of the hedonic pricing model can be shown as follows:

$$\ln R_{it} = \sum_{j=1}^J \beta_j X_{jit} + \sum_{t=1}^T \alpha_t D_{it} + \varepsilon_{it} \quad (1)$$

where R_{it} represents the natural logarithm of the office rent for lease i at time t . X_{jit} denotes the exogenous hedonic attributes, j including property-specific, locational and leasing characteristics. D_{it} is the time dummy variable represents time effect. The office rental index R_t for time period of t is constructed by exponentiating the estimated coefficient from time dummy α_t which can be shown as follows:

$$\hat{R}_t = \exp(\hat{\alpha}_t) \quad (2)$$

Hedonic index is data intensive because it requires detailed information about hedonic attributes. Moreover, the standard hedonic model implicitly assumes market equilibrium. The demand parameter of each characteristic is inferred directly from the estimated coefficient of the equilibrium hedonic equation. In the micro level hedonic model, the variation of office rents is explained by the hedonic attributes. The unexplained variation is assumed to result from model misspecification, omitted variables and a random error. However, this equilibrium hypothesis of the real estate market has been challenged by researchers. The market might deviate from its equilibrium level due to the slow and costly market adjustment process (De Leeuw and Ekanem 1971). Several approaches have been developed to estimate the hedonic model under an assumption of market disequilibrium. Fiar and Jaffee (1972) analyse the determinants of housing supply by incorporating information about price-setting behaviour. Anas and Eum (1984) investigate house prices by using a dynamic price adjustment model and find that these are not only explained by the standard hedonic attributes but also by the market activity signals including macroeconomic variables and past average neighbourhood transaction prices. The main problem of the disequilibrium model is that it is difficult to determine the difference and switching point between equilibrium and disequilibrium. In addition, the aim of the index construction is to reflect the actual movement of the market whether it is in equilibrium or disequilibrium. Therefore, the determination of a market equilibrium level might be irrelevant for the purpose of index construction (Malpezzi 2003).

In addition, the hedonic index also faces the model identification problem. The functional form of the model and regressors that are included in the regression model needs to be determined carefully in order to avoid model misspecification and omitted variable bias (Bourassa, Hoesli and Sun, 2006). Because the complete set of relevant attributes is unobservable, the estimated parameters of the hedonic relationship should be interpreted carefully as all the hedonic models are, to some extent, suffering from misspecification bias (Butler 1982). Thus, the correct functional form and the complete set of real estate attributes remains a challenge for the hedonic model. Empirical research in the real estate literature has suggested a full list of variables to be considered when analysing the hedonic relationship of office rents. Liu, Lizieri and Fuerst (2014) distinguish six categories of attributes by incorporating local and institutional factors. The six categories include property-specific, neighbourhood, locational, leasing, timing and local characteristics.

Repeat sales approach

The repeat sales approach was originally developed by Bailey, Muth and Nourse (1963). The essence of the repeat sales approach is to measure the same asset in two periods while assuming that the

asset attributes do not change over time. The difference in value over two periods is used to identify price movements. It can be viewed as the $(t - \tau)$ th difference of the hedonic pricing model in equation (3) under the assumption that all hedonic attributes are unchanged over the time period of $(t - \tau)$ (Chau, et al, 2005). The standard repeat sales model can be written as follows:

$$R_{it} - R_{i\tau} = \sum_{j=1}^J \beta_j (X_{jit} - X_{ji\tau}) + \sum_{t=1}^T \alpha_t (D_{it} - D_{i\tau}) + (\varepsilon_{it} - \varepsilon_{i\tau}) \quad (3)$$

$$R_{it} - R_{i\tau} = \sum_{t=1}^T \alpha_t D_{it\tau} + \varepsilon_{it\tau} \quad (4)$$

where the subscripts t and τ represent the first leasing and the second leasing of property i , respectively, $(X_{jit} - X_{ji\tau})$ is equal to zero under the assumption of repeat sales approach. $D_{it\tau}$ and $\varepsilon_{it\tau}$ represent $(D_{it} - D_{i\tau})$ and $(\varepsilon_{it} - \varepsilon_{i\tau})$ respectively. The error term $\varepsilon_{it\tau}$ is assumed to be independent and identically distributed.

The advantage of the repeat sales method is that property characteristics data are not required. The only relevant input is the transaction price of the same building for two different time periods. However, this method ignores the property characteristics, it assumes that all property price determinants hold constant across time. This assumption has been criticised by many researchers. It is common that buildings will depreciate with age and this can have a negative impact on both the rent and price of buildings. Moreover, the repeat sales approach only includes properties that have been transacted more than once which may result in inefficient use of the data and sample selection bias as the sample has been selected in a non-random manner (Cheung, Yau and Hui 2004). Gatzlaff and Haurin (1997) show that the degree of sample-selection bias depends on the change of economic conditions. Another assumption of repeat sales indices is that transactions are assumed to be the accurate measurement of market prices. Bourassa, Cantonil and Hoesli (2013) argue that forced sales will distort the repeat sales indices and may not reflect the true market prices. Sales of foreclosed properties by financial institutions often sell at a discount to market value. If the market is dominated by forced sales, as was the case in many US cities during the Global Financial Crisis, the simple remedy of removing them from the sample might not be easy to implement. In addition, the presence of frequently traded and 'flipped' properties might also affect or distort the repeat sales index. Furthermore, this approach also demands more data than the hedonic pricing approach which makes it difficult to apply in emerging markets, especially office markets. Heteroskedasticity is also frequently encountered in repeat sales models possibly due to the larger variation of prices and attributes in the upper market segments but Case and Shiller (1987) present a weighted repeat-sales model (WRS) to overcome this problem. Real Capital Analytics (RCA) adopted the repeat sales approach in developing the UK and US commercial real estate price indices. The Moody's/RCA Commercial Property Price indices (CPPI) are the US commercial property price indices calculated using the repeat sales regression by Moody's based on RCA data. CoStar commercial real estate (CRE) also adopted the repeat sales approach in monitoring the commercial real estate price movement in the US. In order to overcome the bias in the repeat sales regression, CoStar uses the physical

characteristics of properties to distinguish between high value and low value transactions instead of the traditional approach of using all prices.

Hybrid approach

Case and Quigley (1991) introduce a hybrid method that combines both the repeat sales and the hedonic pricing approaches. It removes the assumption of the repeat sales approach by allowing the hedonic attributes to be varied across time. The hybrid approach is expected to be more efficient than both repeat sales and hedonic approaches. However, the availability of repeat sales data has continued to be a challenge, especially in the office market where transactions are infrequent. The hybrid approach also requires information on all relevant hedonic attributes which may be hard to obtain. This approach is data intensive because of the functional form assumption and omitted variable bias (Chau, et al, 2005). It suffers from the same problems encountered in both approaches such as forced sales and immediate second sales and potential misspecification of the hedonic equation.

To sum up, most of the existing real estate index literature focuses on analysing capital values, Case, Pollakowski and Wachter (1991) compared the housing price index construction techniques in the residential market. They found that the repeat sales approach presents more bias and inefficiency problems than the hedonic pricing approach, a hybrid method by comparison, is a superior approach as it avoids most of the bias and inefficiency through the combination of hedonic pricing and repeat sales. Meese and Wallace (1997) found that the hedonic pricing approach is better suited to municipal level data and small sample size than the repeat sales and hybrid indices in the residential market. Clapham, Englund, Quigley and Redfearn (2004) compared the hedonic model and repeat sales indices of house prices and found that the hedonic indices appear to be more stable than the repeat sales index when adjusted for new information. Wu, Deng and Liu (2014) investigated the residential house price index construction in China by comparing the various index construction methods including simple average, matching and hedonic approaches. Their analysis suggested that both simple average and matching techniques are downward biased because they failed to control for both quality changes and developer pricing behaviours compared to the hedonic approach.

Commercial real estate indices in China

There are three main commercial real estate indices providers in the Chinese market: China Index Academy (CIA), CB Richard Ellis and DTZ. Their indices are widely used by both academic researchers and real estate investors.

China Index Academy

The CIA is one of the largest independent real estate research providers in China. It claims to have built cooperative relationships with the National Bureau of Statistics of China, the State Housing Management Bureau, the Real Estate Trading Centre and other government institutions. CIA

developed the China Real Estate Index System (CREIS) to provide timely real estate transaction data in 300 cities. CREIS monitors the monthly transaction-based residential, office and retail real estate indices. The residential indices include new dwellings, hedonic and second-hand price indices and rental indices. CIA developed the residential house price index in 100 cities (HPI-100) in 2009. The index is a transaction-based weighted index to represent the movement of the entire Chinese residential market. The index period for office and retail rental indices is started from 2005. The CIA is one of the principal data providers for the residential real estate market in China. Hui and Yue (2006) adopt the monthly new dwelling indices of Beijing and Shanghai to investigate the housing price determinants in mainland China.

CB Richard Ellis

CB Richard Ellis (CBRE) is a large international commercial real estate service firm. It monitors the performance of residential, office, retail and industrial real estate markets in 14 cities. It publishes the quarterly transaction-based indices for residential, office, retail and industrial real estate markets across Chinese cities. The indices cover the period from the first quarter of 1997 to the present. CBRE entered China in 1988, and has provided the longest coverage of an index compared to other international real estate agencies. Lecomete (2013) adopt the CBRE's quarterly office capital value indices to examine the risk and returns at three Chinese cities. However, those indices are based on valuations in a low liquid market, the accuracy of these indices is still a question as it might suffers from valuation smoothing and lag bias.

DTZ

DTZ is a global real estate service provider and began operating in mainland China in 1993. It divided the commercial real estate market into four categories: office, retail, residential and real estate investment. It publishes the quarterly office and residential capital value and rental indices for major cities in mainland China. According to DTZ's website, the office rental and capital value indices started from the third quarter of 2003 to the present. DTZ's data has been used in recent Chinese real estate market research by Ke and White. They examined the office rental adjustment process in Shanghai in 2009 and further investigated the office rental adjustment process in Beijing and Shanghai by examining the relationship between DTZ's office rental indices and its macroeconomic determinants in 2013. In addition, White and Ke (2014) adopted the DTZ office rental index to investigate the submarket dynamics in Shanghai's Grade A office market. However, DTZ indices might suffer from valuation smoothing and lag bias because it is valuation-based.

3 Data and methodology

Bokhari and Geltner (2012) propose a two-stage frequency conversion approach that converts the lower frequency transaction-based indices into the higher frequency transaction-based indices in a scarce data environment. The first stage is to estimate four staggered annual indices and then convert them into a single quarterly index by applying the generalised inverse estimator. The frequency converted quarterly index is less noise-prone than the direct quarterly index with lower

observed volatility, lower first order autocorrelation and better signal/noise ratio than the annual index. This approach is attractive for creating high-frequency indices in thinly traded markets although it reacts to changes in market conditions more slowly than a pure direct index.

In this study, we adopt Bokhari and Geltner (2012)'s two-stage frequency conversion approach to estimate the quarterly transaction-based rental price index in the Beijing office market for two reasons. Firstly, the direct quarterly index for the Beijing office market cannot be computed because there is insufficient data for certain quarters. The two-stage frequency conversion approach is a powerful tool to construct the high frequency index in a scarce data environment, particularly in emerging markets. Secondly, this technique provides more information than annual indices and has less noise than direct quarterly indices.

First stage of frequency conversion approach

The first stage is to obtain four staggered annual indices from four independent staggered hedonic regressions. We will use the hedonic model specification proposed by Liu, et al (2015) developed specifically for the Beijing office market by incorporating local and institutional factors. The hedonic equation can be expressed as follows:

$$R = f(S, N, L, C, T, U)$$

where R is the office rent, S, N, L, C, T and U represent property-specific, neighbourhood-specific, locational, leasing, timing and local characteristics respectively. Table 1 illustrates the staggered estimation of the hedonic price indices.

Table 1: Creating staggered time dummy variables for estimation in the hedonic model

	Time variable1	Time variable 2	Time variable 3	Time variable 4
Annual dummy	Calendar year CY	Fiscal year to March	Fiscal year to June	Fiscal year to September
Annual period	Q1Y1 to Q4Y1	QY1 to Q1Y2	Q3Y1 to Q2Y2	Q4Y1to Q3Y2

Second stage of frequency conversion approach

The second stage converts the four annual indices into a single quarterly index. It takes the form of a repeat sales regression with a matrix operation. The indices return generated from annual dummies from the four independent staggered hedonic regressions is treated as a set of dummy variables used as regressors. The period of each return, by contrast, is treated as independent binary variables. Because there are fewer rows than columns in the second stage estimation, the system is

underdetermined. There will be infinite solutions and no unbiased estimator exists as there are fewer equations than unknowns. Among the infinite solutions, Moore-Penrose Pseudoinverse can be used to derive the unique solution that minimises the variance of estimated parameters (Penrose, 1955). The estimator using this approach is the Best Linear Minimum Bias Estimator. The estimated equation of the second stage can be written as follows:

$$y = X\beta + \epsilon$$

$$\beta = X^T(XX^t)^{-1}y$$

where y is the $N \times 1$ vector of quarterly index returns, X is a $N \times K$ vector of each period of returns. Because the system is underdetermined, $X^T(XX^t)^{-1}$ returns the Moore-Penrose Pseudoinverse estimation and β is $K \times 1$ vector provide the estimator parameter of quarterly returns.

Data

The hedonic estimation is based on the CBRE Beijing lease transactions database, comprising about a third of professional office leasing activities in Beijing. It is important to note that it contains transactions from domestic, joint ventures and foreign enterprises. SOEs, however, do not routinely use real estate brokerage services which limit the comprehensiveness of CBRE's database. Overall, 392 Beijing office lease transactions are used for estimating the index, covering a fifteen year time span (Q1 1997 to Q4 2012). Rental rates are defined as the net rent per square metre based on gross floor area excluding management fees, rent free periods, and free fitting out periods. Variable definitions are shown in Table 2.

Table 2: variable definition

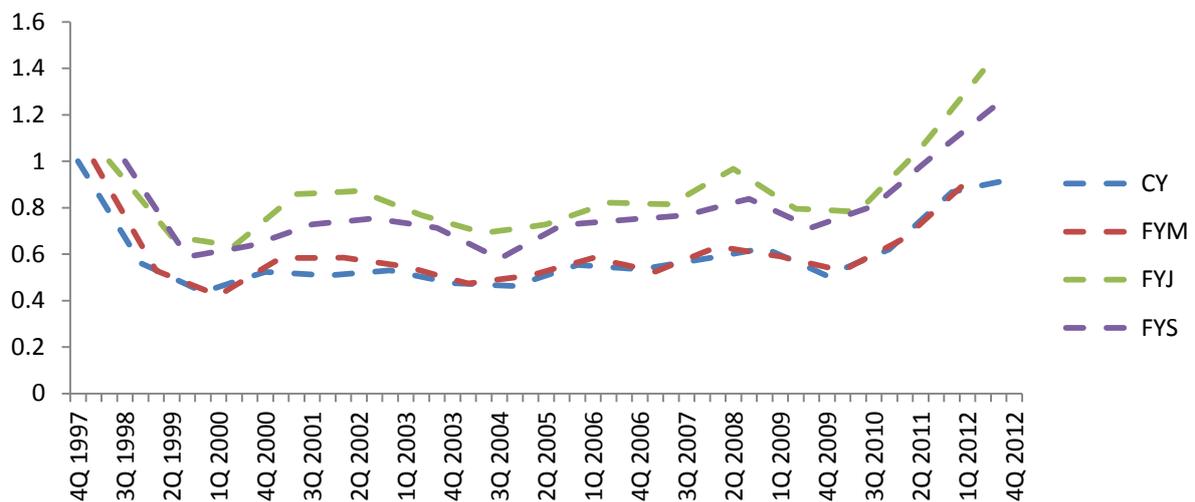
Variable definition	
Continuous variables	
Nominal rent	Measured by per square metre
Real rent	Nominal office rent adjusted by inflation from 1995 based on CEIC data.
Age	The age of the leased office building, measured by number of months
Area	The amount of space that tenant is leased, measured by gross floor area
Building height	The height of the building, measured by the total number of stories
Floor location	The floor that tenant is leased, measured by story
Distance variables	Include distance to airport, distance to the CBD, distance to subway and distance to Tiananmen, measured by kilometre
Lease term	The term of the lease, measured by the total amount of months
Discrete variables	
Submarket variables	Include 9 submarkets: CBD, Jianguomen, Wangfujing, E2R, Lufthansa, Finance street, Zhongguancun, Wangjing and others
Building Grade	Include Grade Premium, Grade A, Grade B and Grade C
Tenant type	Include Foreign, Domestic, JV and SOEs

Developer type	Include Foreign, Domestic, JV and SOEs
Seasonality	Include 4 seasonal dummy variables
Lease clause	equal to 1 if the lease contract has a rent review or break clause option, otherwise 0
Transaction nature	equal to 1 if the lease contract is a renew or expansion lease, new lease equal to 0
Lucky floor	equal to 1 if the leased area is in the 6 th , 8 th , 16 th , 18 th , 26 th , 28 th , 36 th or 38 th , otherwise 0
New Buildings	equal to 1 if the lease contract is signed within one year after the building was completed, otherwise 0

4 Empirical result of index construction

Figure 1 shows the results after the first estimation stage. The four resulting preliminary indices are set to 1 at their respective starting years to facilitate comparison. As can be seen from the graphs, the four indices react with different speed to turning points in the rental growth cycle depending on when these points occur in the year.

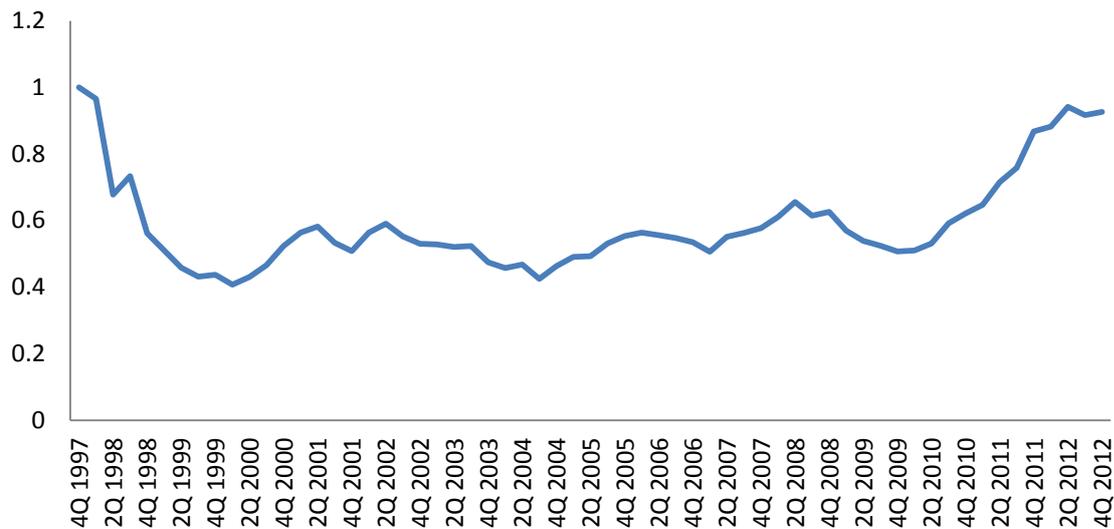
Figure 1: Beijing office market staggered hedonic annual indices



Data source: CBRE Global Research

Next, the four annual indices estimated from the first stage are converted into a single quarterly index. Figure 2 shows the quarterly index constructed by using the two stage frequency conversion approach. Over the 15 year period, the index exhibits a sharp drop in the late 1990s and a marked rise from 2010 onwards.

Figure 2: Beijing office market quarterly office rental price index



5 Robustness check

The lease contract is a negotiation process between tenant and landlord which could be signed at any time during the year. Therefore, the adoption of the annual dummies to aggregate the lease transactions across different time periods might create temporal aggregation bias.

Bryan and Colwell (1982) introduced the concept of fractional dummy variables to overcome the temporal aggregation bias in the repeat sales model. Fisher, Geltner and Pollakowski (2007) extend Bryan and Colwell (1982)'s fractional dummy variables concept so that it could be used in the hedonic pricing model. According to Fisher, et al. (2007), the annual fraction dummy variables are defined as follows: for a transaction that takes place in the q -th calendar quarter of year t , the time-dummy for year t is equal to $1 - (4-q)/4$ and the time-dummy for year $t-1$ is equal to $(4-q)/4$. We adopted the fractional dummy variable approach suggested by Fisher, et al. (2007) as a robust measurement for constructing the rental price index in the Beijing office market. It gives a time weight to each lease transaction to overcome the potential temporal aggregation bias that might be encountered in the standard hedonic model. The regression estimation results by using fractional dummy variables are not significantly different to the standard regression by using standard dummy variables.

6 Index comparisons and risk and return analysis

The direct quarterly transaction-based index cannot be computed currently because of a lack of data. Figure 3 compares the office transaction-based rental indices constructed by using the two stage frequency conversion approach with CBRE's valuation-based indices. ATQ-H and ATQ-F are both annual-to-quarterly indices based on the standard and fractional hedonic models respectively. The CBRE index is a valuation-based index that is constructed from periodic revaluing of the office rents for a group of office buildings in Beijing. It is well recognised that a valuation-based index suffers from the temporal lag bias which results in valuation smoothing of index returns. Therefore, we

adopt the approach developed by Geltner (1993b) to desmooth the CBRE index (Des CBRE in Figure 3 and Table 3). The desmoothing parameter is set to equal to 0.5 as it is the rational or optimal level suggested by Geltner (1993b).

However, most of valuation-based indices are constructed based on capital values rather than on office rents. The valuation desmoothing technique is specifically developed to overcome the temporal lag bias that occurs in valuation-based capital value indices. It is worthwhile to distinguish the feature of the office rental and the capital transaction markets. The former is likely to have more frequent transactions than the latter. The more frequent transactions of office buildings result in more comparable data for the construction of the valuation-based index. In addition, the typical office lease length in China is relatively short, from 2 to 3 years (Fang and Lu, 2009). The short average office lease term results in a timely and accurate estimation of market rents as the contracted rent is updated more frequently. Sales transactions are relatively thin in the Beijing office market. According to CBRE Global Research, only 77 sales were observed between 2005 and 2012. This might be attributed to the restriction of free capital flows and the absence of real estate investment trusts (REITs). Due to higher frequency of transactions and shorter time lags of reporting office rents, it seems reasonable to expect that the valuation smoothing bias is less significant in the office rental market compared to office capital value indices. Therefore, we assume that the CBRE valuation-based index is not severely affected by the temporal lag bias. On the other hand, the revaluation procedure of the CBRE's valuation-based index is based on surveys. Hence, it is not a truly valuation-based index as it relies on the survey from office landlords. Because of the nascent and non-transparent nature of the Beijing office market, it is difficult for the CBRE professionals to achieve accurate and consistent valuation. Therefore, the survey-based CBRE index and the nascent and the early development stage of the Beijing office market make the CBRE index more sensitive and noisy than conventional valuation-based indices which reduce the reliability of the index. According to Bokhari and Geltner (2012), the first order autocorrelation can be used to examine the noise level in index returns. The closer the first order autocorrelation of index returns towards negative 50%, the more noise and worse quality of the index returns.

As can be seen from Figure 3, the movement of both ATQ-H and ATQ-F is very close to both the CBRE and desmoothed CBRE valuation-based rental indices. This suggests that the hedonic model in line with the CBRE index. According to Table 3, the risk/ return characteristics of the valuation-based and transaction-based indices are similar to each other. Both standard and fractional hedonic transaction-based indices and desmoothed CBRE index have slightly higher volatility than the CBRE valuation-based index. The observed high volatility might be explained by both index and market levels. As expected, the smoothing effect is smaller for office rental indices than for office capital value indices. The CBRE index has approximately 2% lower volatility compared to all other indices. This lower volatility is partly due to valuation-smoothing bias in the CBRE index.

Both standard and fractional hedonic models and the desmoothed CBRE index have lower first order autocorrelation than the CBRE index (0.17 and 0.29 compared to 0.74) This is consistent with early findings by Lee, Lizieri and Ward (2000) and Fisher, et al (2007) that a valuation-based index tends to underestimate the volatility and exhibits strong autocorrelation. The relatively high first order autocorrelation of the fractional hedonic model is due to the construction of the index. The time dummy has been constructed by using the fractional weight which gives a time weight for each

transaction which induces autocorrelation. The analysis of the lead-lag relationship shows no clear evidence of a consistent one way leading or lagging effect. Both standard and fractional hedonic indices exhibit a leading effect to the CBRE index, whereas the CBRE index also provides a leading effect to the standard hedonic index based on the Grange Causality test.

Figure 3: the comparison of office rental indices

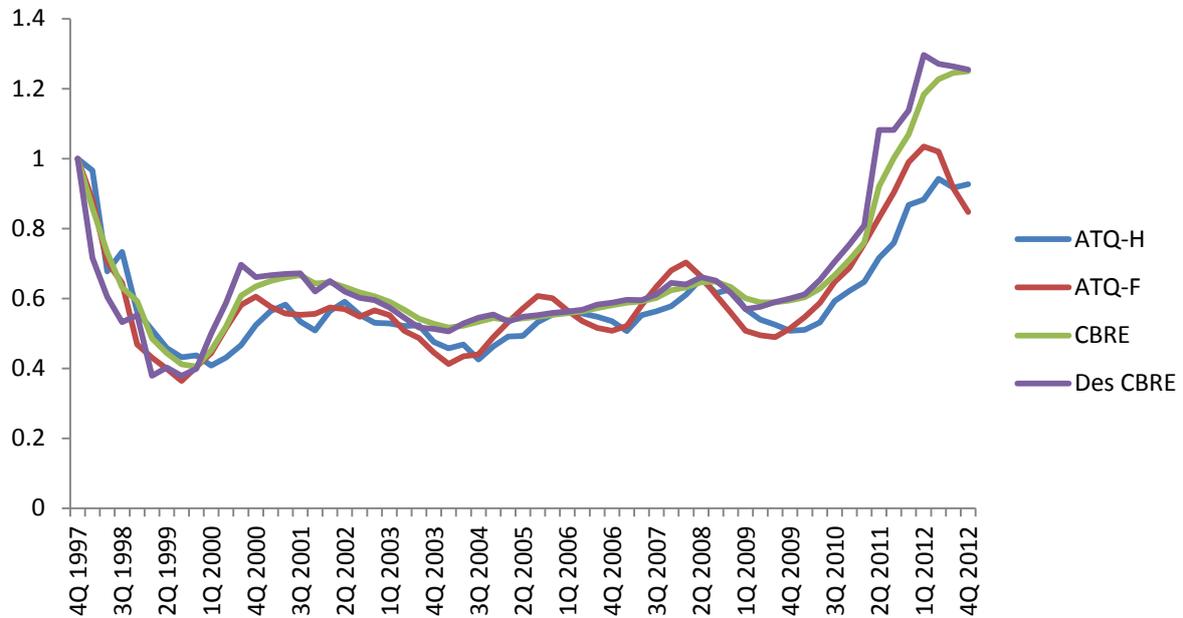


Table 3: the comparison of office rental indices

	Hedonic	Fractional	CBRE	Des CBRE
Risk and return characteristics:				
Arithmetic mean	0.21%	0.09%	0.60%	0.61%
Geometric mean	-0.13%	-0.28%	0.37%	0.13%
Volatility	8.00%	8.50%	6.85%	9.77%
First order autocorrelation:				
AR(1)	0.17	0.68	0.74	0.29
Correlation:				
Hedonic	1.00			
Fractional	0.67	1.00		
CBRE	0.54	0.70	1.00	
Desmoothed CBRE	0.33	0.57	0.88	1.00
Lead-lag relationship				
Lead to CBRE	YES	YES		
Lag to CBRE	YES	NO		
Lead to Des CBRE	NO	YES		
Lag to Des CBRE	YES	NO		
Lead-lag correlation				
One period lead to CBRE	0.54	0.79		

Two period lead to CBRE	0.25	0.60
One period lag to CBRE	0.62	0.59
Two period lag to CBRE	0.57	0.36
One period lead to DesCBRE	0.38	0.62
Two period lead to DesCBRE	-0.05	0.60
One period lag to DesCBRE	0.51	0.58
Two period lag to Desm.CBRE	0.47	0.43

*based on Granger Causality test

7 Conclusion

This paper set out to construct quarterly transaction-based office rental indices for the Beijing office market by adopting a two stage frequency conversion approach. The aim of constructing the transaction-based indices is to complement to the existing valuation-based index by using the real transactions data for the nascent Beijing office market and to provide useful information especially about the timing of market turning points. Given that a transaction-based index does not currently exist there, this analysis provides a useful comparison between quarterly transaction-based and valuation-based indices. The movement of both standard and fractional hedonic indices are very close to the CBRE and the desmoothed CBRE indices. There is no significant deviation between the transaction-based and valuation-based indices which indicates that both approaches have similar view of the market. However, both the standard and fractional hedonic transaction-based indices have slightly higher volatility than the CBRE valuation-based index which provides more timely information about office rental movement. In addition, this paper provides evidence that the index construction methods developed by using the Western market data work well in the market characterised by frequent government intervention, the restriction of free capital flow and planned economy. It also shows that the supply and demand of the office market still remains an important factor in determining the office rent in the Beijing office market. The transaction based indices constructed in this paper provide useful information for real estate investment managers to better understand the risk and return characteristics of the Beijing office market which help them to make more accurate asset allocation decisions. Finally, our research provides a platform for future index construction in other emerging markets. The quarterly transaction-based index obtained by applying the frequency conversion approach can be used to investigate the office rental dynamics with its macroeconomic fundamentals.

8 Bibliography

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9 Appendix

The comparison between effective and asking rental index

Because the CBRE rental index is an asking rental index, we used the nominal asking rent in this paper for consistent and comparable purpose. The following figure and table compare the performance of asking and effective nominal rental index that constructed by using the two-stage frequency conversion approach.

Figure A1: The comparison between asking rental index and effective rental index

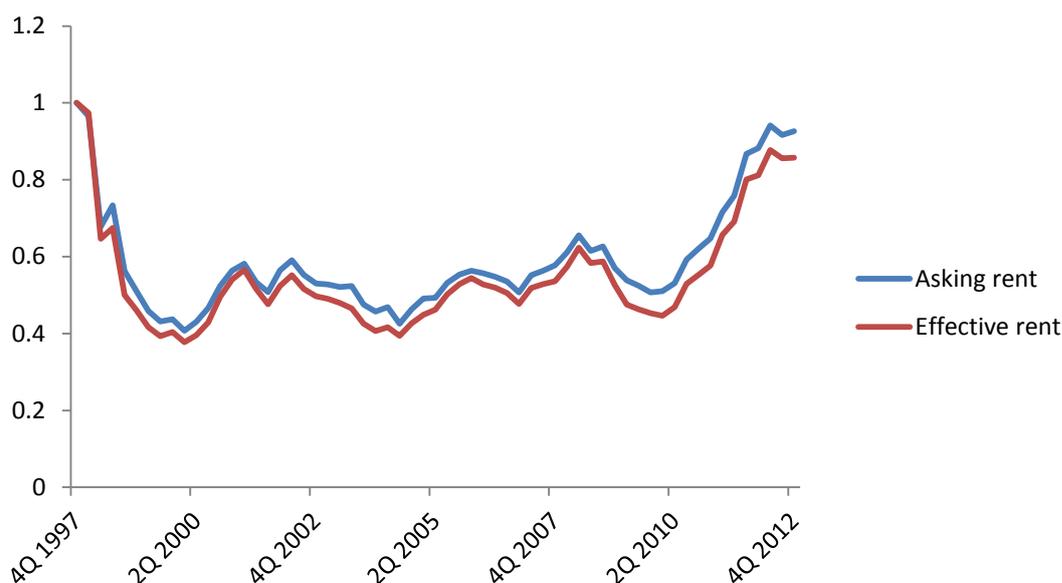


Table A1: index relationship

	Asking rent	Effective rent
Return Characteristics:		
Arithmetic mean change	0.21%	0.15%
Geometric mean	-0.13%	-0.26%
Volatility of change	8.00%	8.69%
First order autocorrelation:		
AR(1)	0.17	0.24
Correlation:		
Asking rent	1.00	
Effective rent	0.98	1.00
Lead-lag relationship		
Lead to effective rent	No	
Lag to effective rent	No	
Lead-lag correlation		
One period lead to effective rent	0.23	
Two period lead to effective rent	0.42	
One period lag to effective rent	0.19	
Two period lag to effective rent	0.43	