Commercial Real Estate Rental Index: A Dynamic Panel Data Model Estimation[*]

A Research Paper Submitted to the Real Estate Research Institute (RERI)

Xudong An[†], Yongheng Deng[‡], and Jeffrey D. Fisher[§]

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[†] Department of Finance, College of Business Administration, San Diego State University, 5500 Campanile Dr., San Diego, CA 92182-8236, e-mail: xan@mail.sdsu.edu.
[‡] Department of Finance, Department of Real Estate, and Institute of Real Estate Studies, National University of Singapore, 21 Heng Mui Keng Terrace, #04-02, Singapore, 119613, e-mail: ydeng@nus.edu.sg.
[§] Department of Finance, Kelly School of Business, Indiana University, 1309 E. Tenth Street, Bloomington, IN 47405-1701, e-mail: fisher@indiana.edu.

1.Introduction

The National Council of Real Estate Investment Fiduciaries (NCREIF) has successfully developed a commercial property price index (NPI) that tracks property value changes. To complement that effort, we develop a rental index based on property-level rent data collected by NCREIF.

Tracking rental rate changes is valuable in a number of ways. First, forming an accurate estimate of rent growth is the first step towards a good forecast of revenues/costs for landlords/tenants. Second, leases are the "engines that drive property value." (Ling and Archer 2009) Therefore, better knowledge about rent growth will help us understand property value dynamics. Third, rent growth directly reflects the space market supply-demand balance/imbalance, and thus is an indicator of opportunities for investors and developers. In fact, because of all the above stated reasons, rent growth is usually one of the key variables that most commercial real estate local forecast will focus on.[1] Comparing to the local rent information usually collected by brokers through surveys, the NCREIF rent data is potentially more representative in terms of property coverage and more consistent in data reporting standards. Therefore, developing rental indices based on the rich NCREIF rent information is potentially a rewarding effort.

Academic research on price index construction can be traced back to at least half a century ago (see, e.g. Bailey, Muth, and Nourse, 1963; Rosen, 1974; Case and Shiller, 1987; 1989; Case and Quigley, 1991; Fisher, Geltner, and Webb, 1994; Calhoun, 1996; England, Quigley, Redfearn, 1999; Fisher, Gatzlaff, Geltner and Haurin, 2003; Geltner, and Pollakowski, 2007; Hwang and Quigley, 2010). A big advantage of the NCREIF rental data over price data is that rents are available in consecutive quarters for a large cross sectional sample of properties. Therefore, unlike the less frequently transacted residential and commercial property price data, we do not need the repeated sales methods most residential price indexes rely on and we can thus avoid the restrictive assumptions of the repeated sales method.[2] Given the availability of the rent time series for each property, an easy to construct rental index will be the cross sectional average of

[1] The other ones include vacancy and net absorption.

[2] For example, a major drawback of the repeated sales method is that it relies on the "sales-pairs" identified during the study period and thus has to assume that revision error due to the repeat sales sample updating is economically and statistically insignificant. See, for example, Deng and Quigley (2008) for a discussion. Moreover, the repeated sales method assumes constant quality of the same property over time.

rental growth. However, important rent determinants such as age of the building can change over time, which leads to a constant-quality problem by the simple average method.

Our approach utilizes recent developments in panel data econometrics and addresses limitations of both the repeated sales method and the simple average approach. We start with a structural decomposition of each property's rent growth into a time-invariant property specific effect (e.g. superior vs. inferior location and amenities), a time-varying property specific effect (e.g. the aging of the property), and a time specific effect, which is the market-wide rent growth (rental index). We then impose a structure on the time series dynamics of the rental index based on space market supply-demand equilibrium. Taking together, a dynamic panel data model with both cross sectional and time series effects is constructed, which avoids the constant-quality assumption problem imposed by the simple average approach and the sample updating problem faced by repeat sales index approach. Meanwhile, it enjoys the usual benefits of panel data models such as increased degree of freedom, identification of dynamic coefficients, and increased estimation efficiency. (Hsiao, 2003)

In fact, the benefits of the dynamic panel data model in terms of increased degree of freedom and identification of dynamic coefficients enable us to estimate the dynamic process of rent growth and thus make forecasting possible. This feature of our model distinguishes our index from the traditional real estate price indexes such as the NPI, the Case-Shiller home price index, and the OFHEO (now FHFA) house price index, which only documents the market trend in the past but keep mute on the future.

Our model also provides a more accurate risk measure of rental income, which is the volatility of the rental index. Apparently, the standard deviation of the cross sectional time series rent growth rate is not a correct risk measure as it contains the cross sectional variation that is diversifiable in a portfolio. Neither does the standard deviation of a time series rental index satisfy that goal because it does not take into consideration the potential autocorrelation in the index.[3]

We estimate our dynamic panel data model with quarterly rent of 9,066 properties during 2001Q2-2010Q2. Our rent growth estimates capture the most recent commercial real estate

3 For example, if the rental growth time series follows a mean-reverting process, then the volatility of rental growth should be the standard deviation of the rental growth multiplied by one minus the square term of the mean-reverting parameter.

market downturn and the previous downturn during 2002-2003. We further find that during the recent recession, decline in rent lags property value depreciation by about a year. This pattern reveals the fact that the recent commercial real estate market downturn was originally led by the collapse of the real estate capital market instead of the space market disequilibrium. Our estimates show that market-wide rent growth is mean-reverting and older properties tend to have consistently lower rent growth.

We estimate separate models for the four major property types and construct rental index for each property type. These indices show very different patterns: apartment is the first to respond to the 2001 recession with rent decline and it experiences the most severe downturn during 2002-2005; industrial properties have seen persistent rent growth and only have slight decline in rent even during the recent crisis. From the risk-return perspective, retail is the worst as it only has moderate long term average rent growth but has the highest rent growth volatility.

We also estimate the rental index for the 5 MSAs that have the largest number of properties in our sample. Among these top 5 MSAs, Chicago, Atlanta, Dallas and Los Angeles closely track each other, while Washington DC stands out as the best performing rental market. It has a long term average log rent growth of 2.8% per year, in contrast to the 0.9-1.2% of the other 4 MSAs.

In addition, we find substantial rent growth premium/discount for certain properties. Across property types, office properties have the highest dispersion in rent premium while apartment buildings have the lowest dispersion, meaning that apartments are more homogeneous than office properties. Based on our model estimates, we construct forecasts of the rental indices for 2010Q3-2011Q2.

In theory, (net) rent growth (or NOI) or should have a negative relation with cap rate. However, existing empirical studies on US commercial real estate cap rate find weak relation between cap rate and rent growth, leading to the speculation of investor irrationality (Hendershott and MacGregor, 2005; Shilling and Sing, 2007). By contrast, we find a strong negative relation between cap rate and our rent growth estimate. There are two possible explanations: 1) investors have better sense of rent growth than of NOI and they incorporate their expectations of rent growth but not of NOI in their valuations, which leads to the weak relation between cap rate and NOI found by some of the existing studies; 2) measurement error and then noise of rent growth data disguise the relation between cap rate and rent growth. Finally, we find a consistent positive relation between NCREIF price return and our rent growth estimate.

Limited efforts have been made on rental index. Torto-Wheaton Research (TWR) produces an index of asking rent based on new leases using data from CB Commercial leasing brokers (Wheaton, Torto, and Southard, 1997).[4] In that effort, a simple regression model, similar to the hedonic price regression, is adopted. Deng, Fisher, Sanders and Smith (2003) apply the repeated sales index methodology to NOI growth based on property-level NOI data[5]. Without fitting time series models to the indices, neither of the aforementioned efforts provides forecasting tools for rent or NOI growth.

The rest of the paper proceeds as follows: in the next section, we present our model and explain the logic behind our model; in section 3 we discuss the data; in section 4 we report our index estimation results as well as the analysis of the rental growth – cap rate relations based on our rental index estimates and forecasts; we conclude in the final section.

2.Rent Growth Model

Consider the rent growth of a particular property in a specific commercial real estate market. It will be largely determined by the supply-demand balance/imbalance of rental space in this market as this property is competing for renters with other similar properties in the same market. Meanwhile, some properties have certain comparative advantages in attracting renters than others. Those comparative advantages could be superior location, easier access, and/or some build-in amenities. Therefore, those properties can have consistently higher rent growth than other properties. Moreover, buildings become aged over time and the conditions can deteriorate over time. Older buildings thus may have lower potential in rent growth. Given these considerations, we decompose the rent growth of a particular property at a particular time into the following:

$$r_{it} = \alpha_i + I_t + \beta \cdot age_{it} + u_{it} \quad (1)$$

[4] There are concerns regarding the representation of the TWR database for the rental index.
[5] See, e.g. Case and Shiller (1987); Englund, Quigley and Redfearn (1999); Clapp (2004); Fisher, Geltner and Webb (1994); Ciochetti, Fisher and Gao (2003), and Cho, Kawaguchi and Shilling (2003) for the repeated sale index construction for both residential and commercial real estate.

where α_i represents the time-invariant property-specific effect due to the property's comparative advantage, I_t represents the time-varying market-wide rent growth, $\beta \cdot age_{it}$ represents the aging effect, and $u_{i,t}$ is an error term that represents the shock to the peculiar property and to the specific time period. We impose the condition that $\sum_i \alpha_i = 0$ so that α_i is relative and thus represents the rent growth premium/discount.

Further consider the market-wide rent growth I_t. The aggregate supply and demand of rental space in a particular market will determine the rent growth, and it is reasonable to assume that adjustments in supply and demand will cause rent growth to fluctuation around a long term mean – when rent growth is high, developers can enter the market to supply more space which will finally bring rent growth down; when rent growth is low, tenants may demand more space which will finally bid rent growth up. Therefore, we assume that I_t will follow the following autoregressive process:

$$I_t = a + \rho I_{t-1} + \varepsilon_t \quad (2)$$

where we expect that $0 < \rho < 1$ to reflect the long term equilibrium and thus the mean-reversion of rent growth due to supply-demand adjustments. The standard deviation of ε_t, σ_ε, is the volatility of the rent growth.

The aforementioned model is intuitive. However, estimation of this model is non-trivial. Let $\alpha_i^* = a + (1-\rho)\alpha_i$ and $\xi_{it} = u_{it} - \rho u_{i,t-1}$, we can rewrite (1) and (2) into:

$$r_{it} = \rho r_{i,t-1} + \alpha_i^* + \varepsilon_t + \xi_{it} + \beta \cdot age_{it} - \rho\beta \cdot age_{i,t-1}, i = 1, \dots, N; t = 2, \dots, T \quad (3)$$

This is a dynamic panel data model with individual specific effect α_i^* and time specific effect ε_t. For this dynamic panel data model, the generalized least squares (GLS) and the generalized method of moments (GMM) estimators proposed by Hsiao and Tahmiscioglu (2008) and Arellano and Bond (1991) can be employed. We discuss the estimation procedure in detail in the appendix.

3.Model Estimates and Rental Index

3.1. Data

In the year of 2000 NCREIF started to collect the detailed rental information (base rent, contingent income, reimbursement income and other income) that is used to calculate the NOI used for the NCREIF property index. We access the NCREIF database to obtain the time series of rental income for nearly 10,000 commercial properties that are located all across the nation. Note that this is different from the NOI that is reported by NCREIF and used for NOI indices produced by NCREIF. We use the rental income that is before deduction of operating expenses. This data has never been used to construct an index of changes in rental rates.

The quarterly rental data starts from 2000Q2 and ends in 2010Q2 (a total of 41 quarters). However, most properties have fewer than 41 quarters of rent information available in our data and different properties have rents available in different quarters. In Table 1, we provide a summary of the rent information availability in our sample. We focus on the four major property types, apartment, industrial, office, and retail. After excluding other property type properties, there are a total of 9,066 properties. On average, 14.5 quarters of rent information is available for these properties. We also provide rent information availability by property type break down. The average length of the rent time series for apartment, industrial, office and retail is 14.5, 15.0, 14.4 and 13.8 quarters, respectively. Chicago, Atlanta, Washington DC, Dallas, and Los Angeles are the 5 MSAs that have the largest number of commercial properties in our sample. We report number of properties and rent information availability also in Table 1.

Based on the rent information, we calculate the 4-quarter log rent growth (year-over-year) of each property in each quarter.[6] We find some unreasonably high or low rent growth in our sample. That could be due to a number of reasons: 1) there is substantial capital expenditure that causes abnormal rent growth; 2) there is addition/expansion in the property which causes extraordinary rent growth; 3) there is data error. Irregular rent growth caused by any of the aforementioned reason is not a reflection of market rent growth. Therefore, we exclude apparent outliers in our sample.

We report the summary statistics of the log rent growth in Table 2 after we exclude the outliers. There are a total of 82,242 property-quarters. On average, these properties have 1.1 percent per year log rent growth during 2001Q3 and 2010Q2. The standard deviation of the 82,242 rent

[6] The calculation of year-over-year (rather than quarter-over-quarter) rent growth is to eliminate any potential seasonal effect in the data.

growth record is 9.6%. Industrial and office properties have higher average rent growth while retail properties and apartments have lower than average rent growth. Apartments have the lowest rent growth dispersion and office properties have the highest dispersion.

The average rent growth varies substantially across MSAs. From Table 2, we see that Washington DC has the highest average rent growth during our study period, 2.5% per year. Atlanta and Dallas both have low average rent growth: 0.3% and 0.4%, respectively. However, the dispersions of rent growth for the 5 MSAs are very close to each other.

3.2. Rent Growth Estimate and Rental Index

In table 3, we report our GLS and GMM estimates of the rent growth model using the whole sample with all property types combined. All the model parameters including a, ρ, β and σ_ε are significant at 99.9% significance level. As expected, ρ is less than 1, indicating that market-wide rent growth is indeed mean-reversion. We calculate the long term average/equilibrium rent growth based on our estimates of a and ρ. Our GLS estimates give us a long term equilibrium log rent growth of 1.0% per year and our GMM estimates give us a long term equilibrium log rent growth of 1.1% per year. The volatility of the rent growth is high, 2.8% from the GLS estimate and 3.7% from the GMM estimate. In our model estimation, instead of using the quarter age of the building, we use an age dummy variable with value of 1 indicating the property is over 5 years old. The coefficient on the building age dummy variable is negative indicating that older buildings do demonstrate smaller rent growth.

In Figure 1, we present our rent growth estimate for each quarter from 2001Q3 to 2010Q2, together with the NPI price return and total return for those quarters from NCREIF. Based on these estimates, we calculate the rental index and present it with the NPI price index in Figure 2. Our rent growth estimates capture the most recent downturn in the commercial real estate market, as well as the downturn during 2002-2003. According to our estimates, US commercial real estate has had positive rent growth during 2001Q3 and 2002Q1. Rental rates start to fall in 2002Q2 and keep falling until 2004Q1. Then we see significant rent growth during 2005-2008. Recently, rental rates start to fall only from the 3rd quarter of 2009. The rental market downturn during 2002-2003 reflects the burst of the dot com bubble and the economic recession in 2001, while the recent downturn reflects the mortgage market and financial crisis as well as the recession starting from the 4th quarter of 2007. Apparently there is a lag in rent growth and recession, which can be due to the fact that commercial real estate leases, especially office, retail and industrial leases are usually long term and thus adjustment of rental income can be sluggish. Comparing the rent growth and NPI returns, we find that during the recent recession, the rent decline lags property value drop by about a year. This pattern reveals the fact that the recent commercial real estate market downturn was originally driven by the collapse of the real estate capital market rather than the space market imbalance. It thus points to the important difference between the commercial real estate space market equilibrium and capital market equilibrium.

In Table 4, we present our estimation results for separate property types. Again, we see that rent growths of all different property types are mean-reversion as $\rho < 1$ for each property type. However, the mean-reverting speed, $1 - \rho$, differs significantly across property types. Retail properties have the highest mean-reverting speed (0.63 based on GLS estimate, and 0.75 based on GMM estimate), followed by industrial (0.56 based on GLS, 0.67 based on GMM), office (0.45 based on GLS, 0.59 based on GMM), and apartments (0.25 based on GLS, 0.34 based on GMM). This pattern seems to be counterintuitive from the supply side of the space market as supply of apartment spaces is usually more elastic than those of retail, industrial and office. However, it could be the low demand elasticity that makes the adjustment of apartment rent growth slower.

Turning to the long term average/equilibrium rent growth, our GLS estimates show that the long term log rent growth for apartment, industrial properties, offices and retail spaces are 0.44%, 1.34%, 1.33%, and 0.73%, respectively. The GMM estimates are 0.54%, 1.38%, 1.50% and 0.72%, respectively for those four property types following the aforementioned order. Therefore, the long term average rent growths are substantially different for different property types. Our volatility estimates are also significantly different for the four property types: GLS estimates of 1.52%, 3.11%, 2.48%, and 4.33%, and GMM estimates of 2.17%, 3.88%, 3.43%, and 5.21%. Apparently, the estimated volatilities are significantly smaller than the standard deviations of the rent growth reported in Table 2 (7.4%, 10.2%, 10.6%, and 9.6%). From the risk-return perspective, retail is the worst as it only has moderate long term average rent growth but has the highest rent growth volatility.

Regarding the age effect, industrial and office properties still demonstrate a strong impact of building age: older properties have significantly lower rent growth. However, it is interesting to see that apartment and retail properties demonstrate a pattern that is contrary to the aforementioned pattern. A possible explanation is that apartment complexes and shopping centers only become mature after a few years and start to attract a stable stream of tenants.

To further see the difference in rent growth between different property types, we plot the rental indices of the four property types in Figures 3 and 4. The differences are prominent. During the 2002-2003 downturn, apartment rent is the first to fall in 2001Q4 while office rent starts to fall only in 2003Q1. This is possibly due to the lease term we discussion earlier: office leases are usually 3-5 years while apartment leases are usually short term. Therefore, apartment rental rates respond to the economic recession much more quickly than office rents. Industrial rents have seen persistent growth and only have slight decline even during the recent crisis. Over the entire 10-year period, office properties have accumulated the highest rent growth.

In table 5, we present our model estimates for the top 5 MSAs: Chicago, Atlanta, Washington DC, Dallas, and Los Angeles. All model parameters for all MSAs, except the age effect for Los Angeles are significant at the 99.9% significance level. Again, in each of the aforementioned market, rent growth is mean-reverting, and the mean-reversion parameters are similar for all the 5 MSAs. In terms of long term average log rent growth, Chicago, Atlanta, Dallas, and Los Angeles are close at the range of 0.91-1.18% per year based on the GLS estimates and 0.87-1.11% per year based on GMM estimates. However, Washington DC stands out as the best performing rental market with a long term average log rent growth of 2.8% per year. The volatilities of rent growth for the 5 MSAs are similar.

In Figures 5 and 6, we plot the rental index for the top 5 MSAs based on the aforementioned rent growth estimates. Again, we see that Washington DC stands out with extraordinary rent growth during our study period, although all 5 MSAs see rent decline during the recent crisis.

We report the distribution of our rent growth premium/discount estimates of individual properties in Table 6. We see that some properties have significant higher/lower rent growth than the population at large. For example, the office property at the 95 percentile has 6.4% per annum higher rent growth than the average property while at the office building at the 5 percentile has

6.3% per annum lower rent growth than average. In future studies, it may be worth to investigate what causes those rent premiums and discounts. One may want to link those premiums and discounts to detailed property characteristics such as location, ease of access, size, walkability, greeness, etc. In terms of cross-property type comparisons, office properties have the highest dispersion in rent premium while apartment buildings have the lowest dispersion in rent premium, meaning that apartments are more homogeneous than office properties.

Our model not only allows us to track the history of market-wide rent growth, it also enables us to make predictions into the future. We plot our forecasts of the rental index from 2010Q3 to 2011Q2 by property type in Figures 7-10. The red line shows our estimates of the historical rental index, the green line shows our forecasts and the purple dots show the confidence band of our forecasts.

4. Rent Growth, Cap Rate and Price Return

In theory, rent growth has a negative relation with cap rate. In a static Gordon (1962) model, cap rate is the difference between return and rental growth, i.e.,

$$\mathrm{c} = \mathrm{R} - \mathrm{r}. \tag{17}$$

Recent studies including Shilling and Sing (2007), An and Deng (2009), Plazzi, Torous and Valkanov (2010) apply the Campbell and Shiller (1989) price-dividend model to commercial real estate and establish the relation between cap rate and rent growth in a dynamic setting:

$$c_t \simeq E_t \sum_{j=1}^{\infty} \rho^{j-1} \left(r_{t+j} - g_{t+j} \right) - \frac{k}{1-\rho}. \tag{18}$$

However, the existing literature on cap rate has not confirmed the relation between cap rate and rent growth. Earlier studies such as Hendershott and Turner (1996) and Chichernea, Miller, Fisher, Sklarz and White (2008) discuss rent growth as a determinant of cap rate but do not include rent growth in the empirical analysis. Recent studies try to estimate the relation between commercial real estate cap rate, return, and rent growth but find that the relation between cap rate and (net) rent growth/NOI tends to be weak if there is any. For example, Shilling and Sing (2007) estimate a set of VAR models using the Korpacz survey cap rate, NCREIF return, and a proxy of net rent growth from NCREIF property income growth. They find virtually no statistically significant relation between cap rate and net rent growth. Clayton, Ling and Naranjo (2009) mainly look at the RERC survey cap rate, expected return, and expected rent growth. Through OLS regressions and vector error correction models, they find very limited relation between cap rate and rent growth. Using the GRA data on average cap rate and rent growth and the REITs return data, Plazzi, Torous and Valkanov (2010) find that, among the four major property types, only office properties data demonstrate a significant relation between rent growth and cap rate.

Since we have estimated rent growth based on NCREIF data, we further collect data on NCREIF cap rate and return, and examine the relations between rent growth and cap rate and return.

We first run the following predictive regressions following Plazzi, Torous and Valkanov (2010):

$$r_{i,t+l} = a_i + \gamma c_{i,t} + \varepsilon_{i,t+l}, \qquad i = 1, \dots, N;\ t = 1, \dots, T;\ l = 1, 2, 3, 4, \qquad (19)$$

where $c_{i,t}$ is the cap rate for property type i in quarter t, and $r_{i,t+l}$ is the l-quarter lead of rent growth for the same property type. The logic behind this regression is that if cap rate contains information about future rent growth as described in equation (18), then it should be predictive of future rent growth.

We report the results of the panel data regression in Table 7. We see that lagged cap rate has a strong negative relation with our rent growth estimate, suggesting that cap rate is actually informative of future rent growth. We also see that the magnitude of the coefficients degenerates as cap rate goes far back to the past (equivalently rent growth does far into the future), which is completely consistent with the theoretical relation in equation (18).

Next, we analyze the relation between cap rate and rent growth from a different perspective: from equation (18), we see that cap rate is determined by expected future return and expected future rent growth. If investors have rational expectations that future rent growth will be mean-reverting due to space market supply-demand adjustments, then all their expected future rent growth will be based on the current rent growth. Further, rational investors will form their valuation according to equation (18). Therefore, we can test the rational expectations hypothesis by examining the relation between cap rate and current rent growth.

We run a rational expectation model in the following form:

$$c_{i,t} = a_i + \gamma r_{i,t} + X_{i,t}\eta + \varepsilon_{i,t}, \qquad (20)$$

where $c_{i,t}$ is the cap rate for property type i in quarter t, $r_{i,t}$ is the rent growth for the same property type, and $X_{i,t}$ are other explanatory variables.

In Table 8, we present our panel data regression results. In various specifications, we experiment several other explanatory variables in addition to rent growth. The survey commercial mortgage interest rate is constructed as the 10-year Treasury rate plus the mortgage spread (by property type) from surveys conducted by RealtyRates.com. The NCREIF commercial mortgage interest rate is the average mortgage interest rate of NCREIF properties. The bank tightening commercial real estate credit is the net percentage of survey respondents claiming tightened credit for commercial real estate from the Federal Reserve senior loan officer survey. CMBS issuance is the volume of new CMBS issuance reported by the Commercial Mortgage Securities Association (CMSA). In all 5 specifications, rent growth demonstrates a strong negative relation with cap rate, consistent with the rational expectations hypothesis. As expected, mortgage interest rate as a measure of the cost of debt and thus part of the expected return is positively correlated with cap rate. Moreover, when banks tighten their commercial real estate credit, or when the CMBS market shrinks, cap rate goes up due to more difficult financing. Based on the adjusted R-square, we also notice that rent growth together with mortgage interest rate and availability of financing well explains cap rate for our study period. The 4 variables explain 85% of the cap rate variations.

Finally, we analyze the relation between rent growth and NCREIF price return by running the following regression:

$$p_{i,t} = a_i + \gamma r_{i,t} + X_{i,t}\eta + \varepsilon_{i,t}, \qquad (21)$$

where $p_{i,t}$ is the price return for property type i in quarter t, $r_{i,t}$ is the rent growth for the same property type, and $X_{i,t}$ are other explanatory variables.

We present the panel data regression results in Table 9. Interestingly, we find a consistent positive relation between NCREIF price return and our rent growth estimate in various specifications. We believe this finding is consistent with the rational expectations theory:

investors have reasonable expectation about rent growth and they price properties based on that expectation. Therefore, price return and rent growth is linked through expected rent growth.

5. Conclusions

We construct commercial real estate rental index using a dynamic panel data econometric modeling approach. The dynamic panel data model allows us to decompose the cross sectional and time series effects of the rental growth, and impose a structure on the time series dynamics of the rental index based on space market supply-demand equilibrium. The new dynamic panel data model avoids the constant-quality assumption problem imposed by the simple average approach and the restrictive error term problem faced by repeat sales index approach. Meanwhile, it enjoys the usual benefits of panel data models such as increased degree of freedom, identification of dynamic coefficients, and increased estimation efficiency. The model provides a more accurate risk measure of rental income, which is the volatility of the rental index. The new model also enables us to estimate the dynamic process of rent growth and thus allows us to make predictions into the future.

We find that during the recent recession in our sampling period, decline in rent lags property value depreciation by about a year. This pattern reveals the fact that the recent commercial real estate market downturn was originally led by the collapse of the real estate capital market instead of the space market disequilibrium. Our estimates show that market-wide rent growth is mean-reverting and older properties tend to have consistently lower rent growth.

Our estimates show rental growth varies across commercial real estate sectors: apartment is the first to respond to the 2001 recession with rent decline and it experiences the most severe downturn during 2002-2005; industrial properties have seen persistent rent growth and only have slight decline in rent even during the recent crisis. From the risk-return perspective, retail is the worst as it only has moderate long term average rent growth but has the highest rent growth volatility.

We find substantial rent growth premium/discount for certain properties. Across property types, office properties have the highest dispersion in rent premium while apartment buildings have the lowest dispersion, meaning that apartments are more homogeneous than office properties. Based on our model estimates, we construct forecasts of the rental indices for 2010Q3-2011Q2.

We also find that among the top 5 MSAs that have the largest number of properties in our sample, Chicago, Atlanta, Dallas and Los Angeles closely track each other, while Washington DC stands out as the best performing rental market. It has a long term average log rent growth of 2.8% per year, in contrast to the 0.9-1.2% of the other 4 MSAs.

Expected rent growth is an important determinant of cap rate in theory. However, existing literature finds that commercial real estate cap rate in US has a weak relation with rent growth, which leads to the speculation of investor irrationality. Interestingly, we find a strong negative relation between cap rate and our rent growth estimate. Finally, we find a consistent positive relation between NCREIF price return and our rent growth estimate in various specifications.

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Appendix: Estimation Procedure for the Rent Growth Model

Taking first difference of (3), we have

$$\Delta r_{it} = \rho \Delta r_{i,t-1} + \Delta \varepsilon_t + \Delta \xi_{it} + \beta(1-\rho) \text{ , with } i = 1, \ldots, N; t = 3, \ldots, \quad (4)$$

Let $\Delta r_t = \frac{1}{N}\sum_{i=1}^{N} \Delta r_{it}$, $\Delta \xi_t = \frac{1}{N}\sum_{i=1}^{N} \Delta \xi_{it}$, and take deviation of Δr_{it} from Δr_t yields

$$(\Delta r_{it} - \Delta r_t) = \rho(\Delta r_{i,t-1} - \Delta r_{t-1}) + (\Delta \xi_{it} - \Delta \xi_t), \ i = 1, \ldots, N; \ t = 3, \ldots, T \quad (5)$$

Finally, let $\Delta r_{it}^* = \Delta r_{it} - \Delta r_t$, $\Delta \xi_{it}^* = \Delta \xi_{it} - \Delta \xi_t$. Assume $\xi_{it} \sim N(0, \sigma_\xi{}^2)$ and treat $\Delta r^*{}_{i2} = \Delta \xi^*{}_{i2}$ as in Hsiao and Tahmiscioglu (2008), we have the following two estimators:

The Generalized Least Squares Estimator (GLS)

Let $\Delta \underset{\sim}{r}_i^{*'} = (\Delta r^*{}_{i2}, \ldots, \Delta r^*{}_{iT})$, $\Delta \underset{\sim}{r}_{i,-1}^{*'} = (0, \Delta r^*{}_{i2}, \ldots, \Delta r^*{}_{i,T-1})$ and $\Delta \underset{\sim}{\xi}_i^{*'} = (\Delta \xi^*{}_{i2}, \ldots, \Delta \xi^*{}_{iT})$.

Stacking all N cross-sectional individuals' time series observations together yields

$$\underset{NT\times 1}{\Delta \underset{\sim}{r}^*} = \begin{pmatrix} \Delta \underset{\sim}{r}_1^* \\ \vdots \\ \Delta \underset{\sim}{r}_N^* \end{pmatrix} = \begin{pmatrix} \Delta \underset{\sim}{r}_{1,-1}^* \\ \vdots \\ \Delta \underset{\sim}{r}_{N,-1}^* \end{pmatrix} \rho + \begin{pmatrix} \Delta \underset{\sim}{\xi}_1^* \\ \vdots \\ \Delta \underset{\sim}{\xi}_N^* \end{pmatrix} = \Delta \underset{\sim}{r}_{-1}{}^* \rho + \Delta \underset{\sim}{\xi}^* \quad (6)$$

It is known that

$$E(\Delta \underset{\sim}{\xi}_i^*) = \underset{\sim}{0}, \ E(\Delta \underset{\sim}{\xi}_i^* \Delta \underset{\sim}{\xi}_i^{*'}) = \sigma_\xi^2 (1 - \frac{1}{N}) A, \ E(\Delta \underset{\sim}{\xi}_i^* \Delta \underset{\sim}{\xi}_j^{*'}) = \sigma_\xi^2 (-\frac{1}{N}) A, \ \ i \neq j$$

Therefore,

$$E(\Delta \underset{\sim}{\xi}^* \Delta \underset{\sim}{\xi}^{*'}) = \sigma_\xi^2 (Q \otimes A) = \sigma_\xi^2 \Omega$$

where

$$A = \begin{pmatrix} \omega & -1 & 0 & 0 & . & 0 \\ -1 & 2 & -1 & 0 & . & . \\ 0 & -1 & 2 & -1 & . & . \\ . & . & . & . & . & . \\ . & . & . & . & 2 & -1 \\ 0 & . & . & . & -1 & 2 \end{pmatrix},$$

If ω is unknown, it may be substituted by a consistent estimator $\widehat{\omega} = \frac{2}{1+\widehat{\rho}}$, where $\widehat{\rho}$ is some initial consistent estimator of ρ.

$Q = I_N - \frac{1}{N} \underset{\sim}{e}_N \underset{\sim}{e}_N^{'}$, $\underset{\sim}{e}_N$ is an $N \times 1$ vector of ones.

Since Q is idempotent, the Moore-Penrose inverse of Ω is $\Omega^{-} = (Q \times A^{-1})$. Therefore, the generalized least squares estimator (GLS) is

$$\widehat{\rho}_{GLS} = \left[\Delta \underset{\sim}{r}_{-1}^{*'} \Omega^{-} \Delta \underset{\sim}{r}_{-1}^{*'} \right]^{-1} \left[\Delta \underset{\sim}{r}_{-1}^{*'} \Omega^{-} \Delta \underset{\sim}{r}^{*'} \right]$$

$$= \left[\sum_{i=1}^{N} \Delta \underset{\sim}{r}_{i,-1}^{*'} A^{-1} \Delta \underset{\sim}{r}_{i,-1}^{*'} \right]^{-1} \left[\sum_{i=1}^{N} \Delta \underset{\sim}{r}_{i,-1}^{*'} A^{-1} \Delta \underset{\sim}{r}_{i}^{*'} \right] \quad (7)$$

Feasible GLS (FGLS) is calculated when ω is substituted by $\widehat{\omega}$.

The Generalized Method of Moments (GMM) estimator

Equation (5) satisfies the moments conditions

$$E(r_{i,t-j} \Delta \xi^{*}_{it}) = 0 \quad \text{j} = 2, \ldots, (\text{t} - 1); \text{t} = 3, \ldots, \text{T} \quad (8)$$

Stacking the first-differenced equations in matrix forms, we have:

$$\Delta \underset{\sim}{\tilde{r}}_i^{*} = \Delta \underset{\sim}{\tilde{r}}_{i,-1}^{*} \rho + \Delta \underset{\sim}{\tilde{\xi}}_i^{*}, \text{ i} = 1, \ldots, \text{N} \quad (9)$$

where

$\Delta \underset{\sim}{\tilde{r}}_i^* = (\Delta r^*_{i3}, \ldots, \Delta r^*_{iT})'$, $\Delta \underset{\sim}{\tilde{r}}_{i,-1}^* = (\Delta r^*_{i2}, \ldots, \Delta r^*_{i,T-1})'$, $\Delta \underset{\sim}{\tilde{\xi}}_i^* = (\Delta \xi^*_{i3}, \ldots, \Delta \xi^*_{iT})'$.

Then the $\frac{1}{2}(T-1)(T-2)$ orthogonality conditions can be represented as

$$E(W_i \Delta \underset{\sim}{\tilde{\xi}}_{it}^*) = \underset{\sim}{0} \tag{10}$$

where

$$W_i = \begin{pmatrix} \underset{\sim}{q}_{i3} & \underset{\sim}{0} & \cdots & \underset{\sim}{0} \\ \underset{\sim}{0} & \underset{\sim}{q}_{i4} & & \\ \vdots & \vdots & \ddots & \\ \underset{\sim}{0} & \underset{\sim}{0} & & \underset{\sim}{q}_{iT} \end{pmatrix}, \text{ i} = 1, \ldots, \text{N}; \ \underset{\sim}{q}_{it} = (r_{i1}, r_{i2}, \ldots, r_{i,t-2})', \text{ t} = 3, \ldots, \text{T}.$$

Following Arellano and Bond (1991), we can estimate a GMM estimator of ρ:

$$\widehat{\rho}_{GMM} = \left\{ \left[\frac{1}{N} \sum_{i=1}^{N} \Delta \underset{\sim}{\tilde{r}}_{i,-1}^{*'} W'_i \right] \widehat{\psi} \left[\frac{1}{N} \sum_{i=1}^{N} W_i \Delta \underset{\sim}{\tilde{r}}_{i,-1}^* \right] \right\}^{-1} \left\{ \left[\frac{1}{N} \sum_{i=1}^{N} \Delta \underset{\sim}{\tilde{r}}_{i,-1}^{*'} W'_i \right] \widehat{\psi} \left[\frac{1}{N} \sum_{i=1}^{N} W_i \Delta \underset{\sim}{\tilde{r}}_i^* \right] \right\} \tag{11}$$

where $\widehat{\psi} = \widehat{\sigma}_{\xi}^2 \left[\sum_{i=1}^{N} W_i \widetilde{A} W_i' \right]$, $\underset{(T-2)\times(T-2)}{\widetilde{A}} = \begin{pmatrix} 2 & -1 & 0 & 0 & . & 0 \\ -1 & 2 & -1 & . & . & . \\ 0 & -1 & 2 & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & 2 & -1 \\ 0 & . & . & . & -1 & 2 \end{pmatrix}$,

and $\hat{\sigma}_{\xi}^2$ is some initial consistent estimator of σ_{ξ}^2.

Estimation of α, β and σ_{ε}^2

Once an FGLS or GMM estimator of ρ is obtained, we can obtain a more efficient $\hat{\sigma}_{\xi}^2$ with the residuals of (6) or (9).

We can also retrieve α by rearranging equation (3):

$$r_{it} - \rho r_{i,t-1} = a + \left[(1-\rho)\alpha_i + \varepsilon_t + u_{i,t} - \rho u_{i,t-1}\right] + \beta \cdot age_{it} - \rho\beta \cdot age_{i,t-1}. \quad (12)$$

Denoting $\gamma_{it} = r_{it} - \rho r_{i,t-1}$, $\delta_{it} = (1-\rho)\alpha_i + \varepsilon_t + u_{i,t} - \rho u_{i,t-1}$, then (12) becomes:

$$\gamma_{it} = a + \delta_{it} + \beta(age_{it} - \rho \cdot age_{i,t-1}) \quad (13)$$

Since $(\delta_{it}) = E\left[(1-\rho)\alpha_i + \varepsilon_t + u_{i,t} - \rho u_{i,t-1}\right] = 0$, a and β can be obtained from a regression of γ_{it} on a $N(T-1) \times 1$ vector of ones and $(age_{it} - \hat{\rho} \cdot age_{i,t-1})$.

Summing up (3) across the individuals, we obtain:

$$\frac{1}{N}\sum_{i=1}^{N} r_{it} = \rho \frac{1}{N}\sum_{i=1}^{N} r_{i,t-1} + a + \frac{1}{N}\sum_{i=1}^{N} \alpha_i + \varepsilon_t + \frac{1}{N}\sum_{i=1}^{N} \xi_{it} + \frac{1}{N}\sum_{i=1}^{N}\left(age_{it} - \hat{\rho} \cdot age_{i,t-1}\right) =$$
$$\rho \frac{1}{N}\sum_{i=1}^{N} r_{i,t-1} + a + \varepsilon_t + \frac{1}{N}\sum_{i=1}^{N} \xi_{it} + \frac{1}{N}\sum_{i=1}^{N}\left(age_{it} - \hat{\rho} \cdot age_{i,t-1}\right),\ t = 2, \ldots, T, \quad (14)$$

where the second equality follows from the restriction that $\sum_{i=1}^{N} \alpha_i = 0$.

Rearranging (14), we have:

$$\varepsilon_t + \frac{1}{N}\sum_{i=1}^{N} \xi_{it} = \frac{1}{N}\sum_{i=1}^{N} r_{it} - \rho \frac{1}{N}\sum_{i=1}^{N} r_{i,t-1} - a - \frac{1}{N}\sum_{i=1}^{N}(age_{it} - \hat{\rho} \cdot age_{i,t-1}) \quad (15)$$

$Var(\varepsilon_t + \frac{1}{N}\sum_{i=1}^{N} \xi_{it})$, hence, can be estimated. Since $\hat{\sigma}_{\xi}^2$ has been calculated in the estimation of ρ, $\hat{\sigma}_{\varepsilon}^2$ can be estimated as:

$$\hat{\sigma}_{\varepsilon}^2 = \widehat{Var(\varepsilon_t + \frac{1}{N}\sum_{i=1}^{N} \xi_{it})} - \frac{1}{N}\hat{\sigma}_{\xi}^2 . \quad (16)$$

With β estimated and the condition that $\sum_i \alpha_i = 0$, a sequence of the rent growth $\widehat{I_t}$ can be calculated from equation (1).

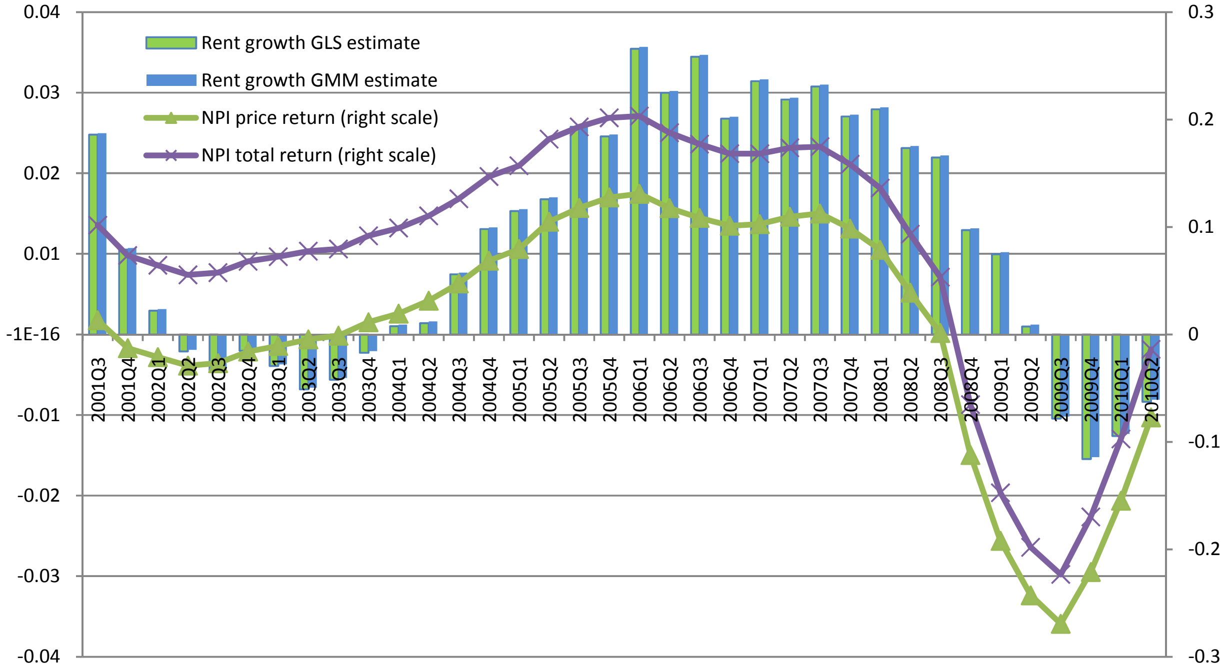

Figure 1 Rental Growth Estimates and NPI Returns (All property types combined)

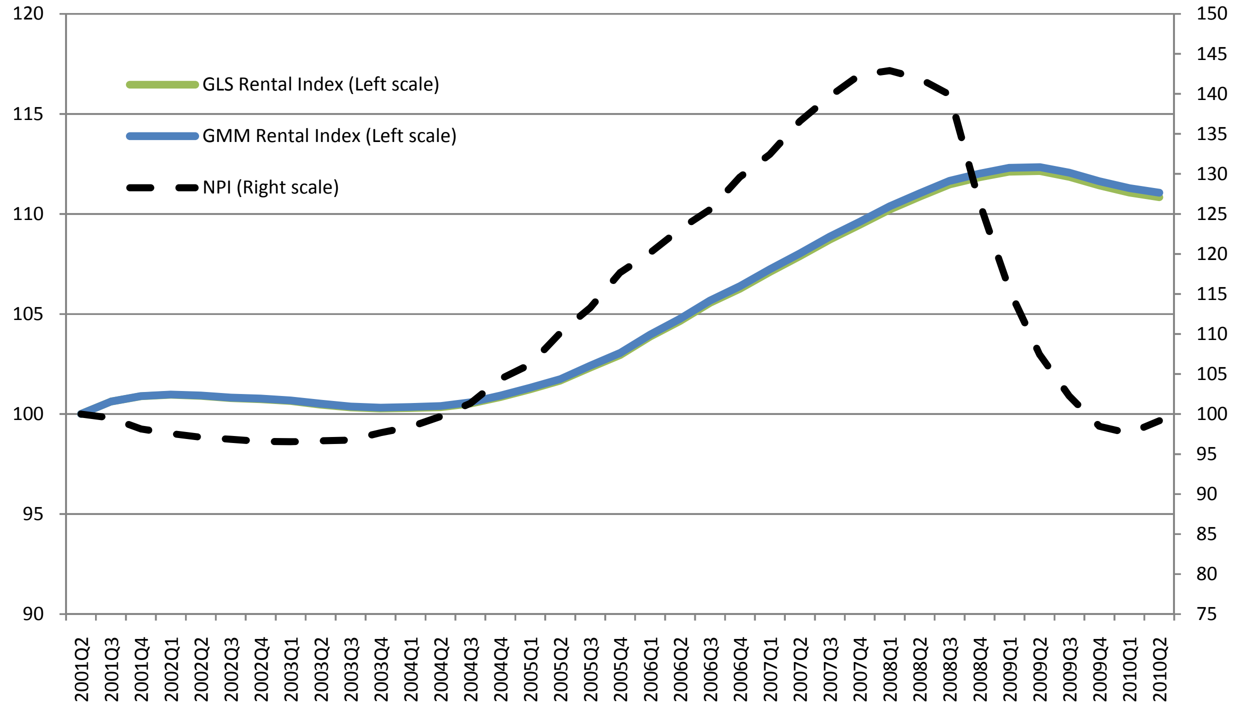

Figure 2 Rental Index and NPI (All Property Types Combined)

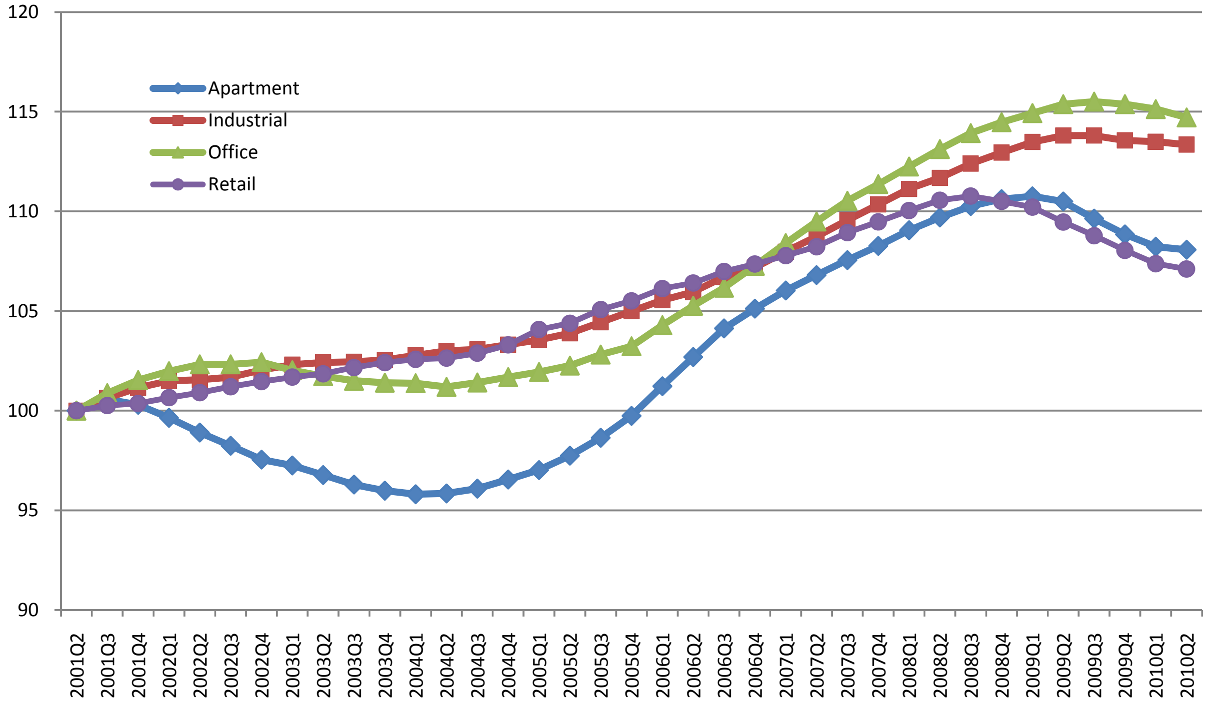

Figure 3 Rental Index by Property Type (GLS Estimates)

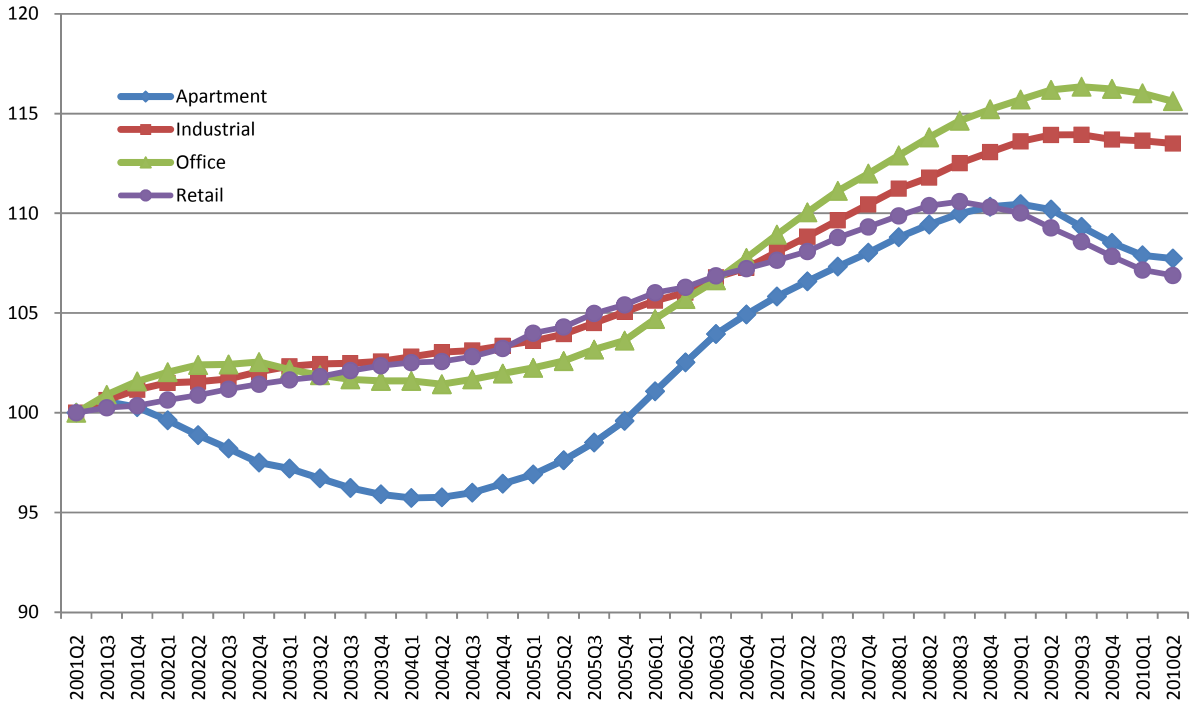

Figure 4 Rental Index by Property Type (GMM Estimates)

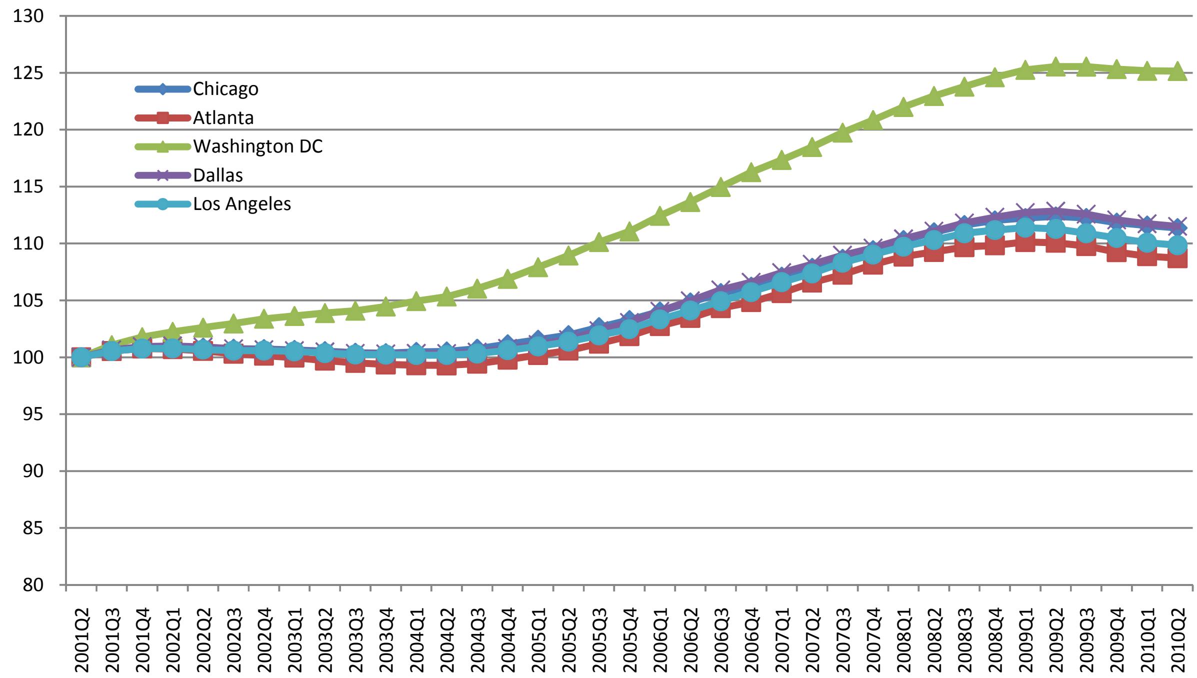

Figure 5 Rental Indices of the Top 5 MSAs (GLS Estimates)

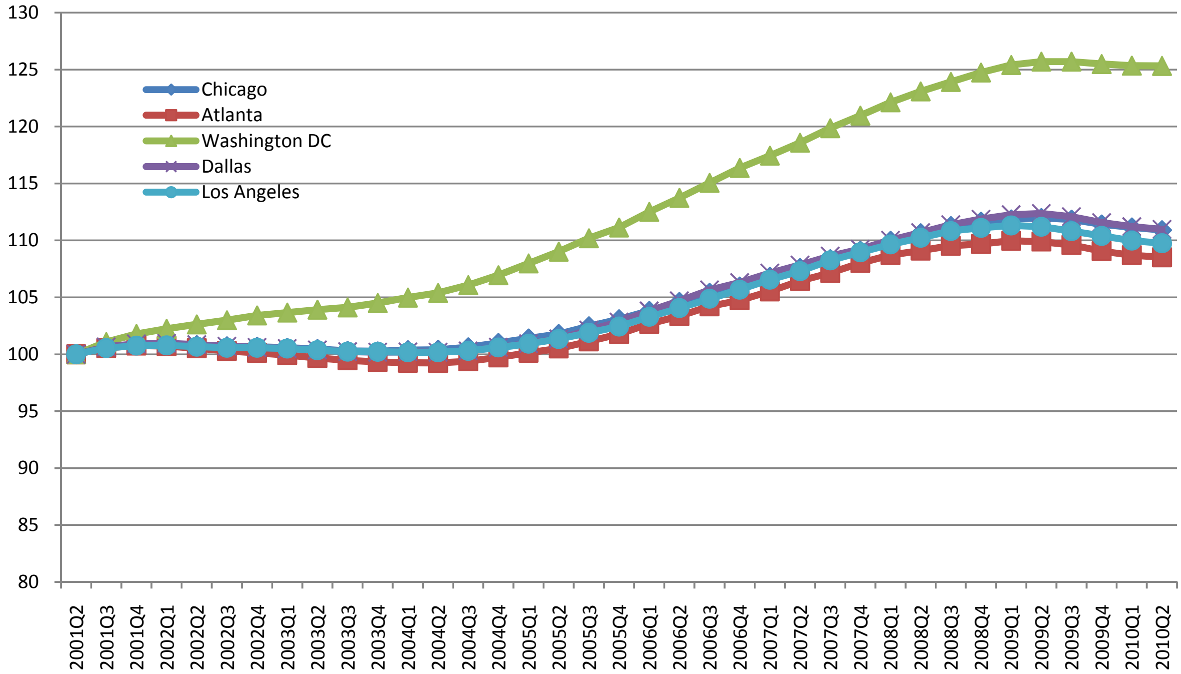

Figure 6 Rental Indices of the Top 5 MSAs(GMM Estimates)

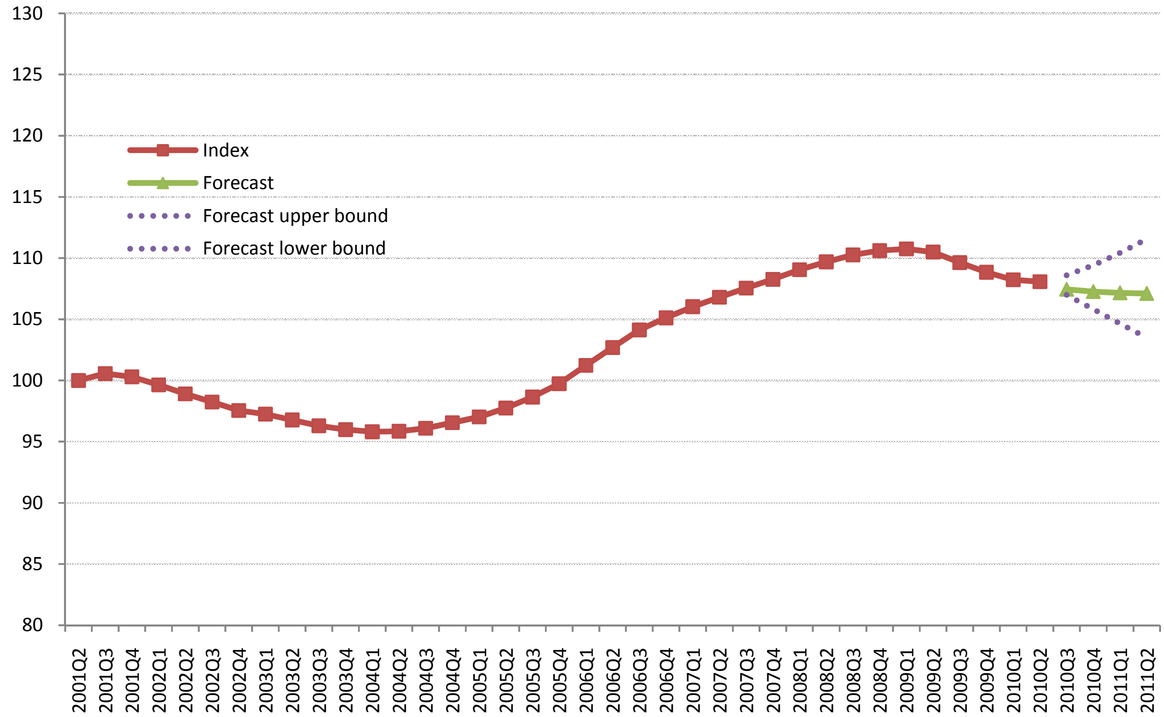

Figure 7 Apartment Rental Index and its Forecast

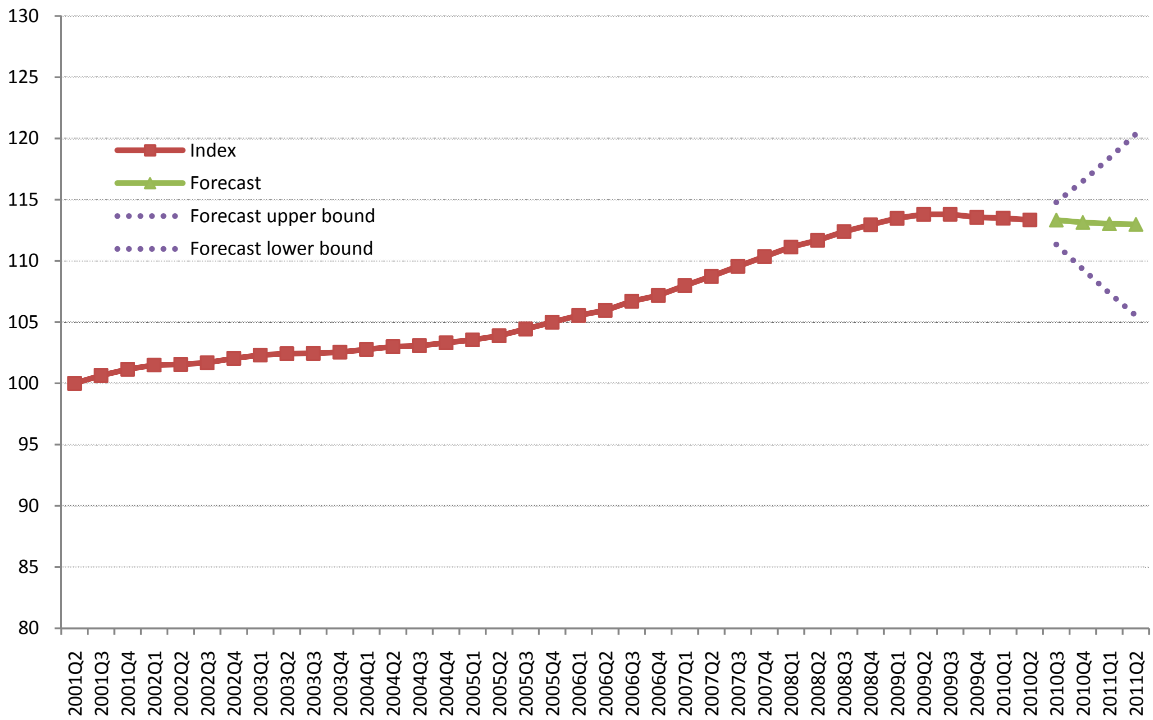

Figure 8 Industrial Rental Index and its Forecast

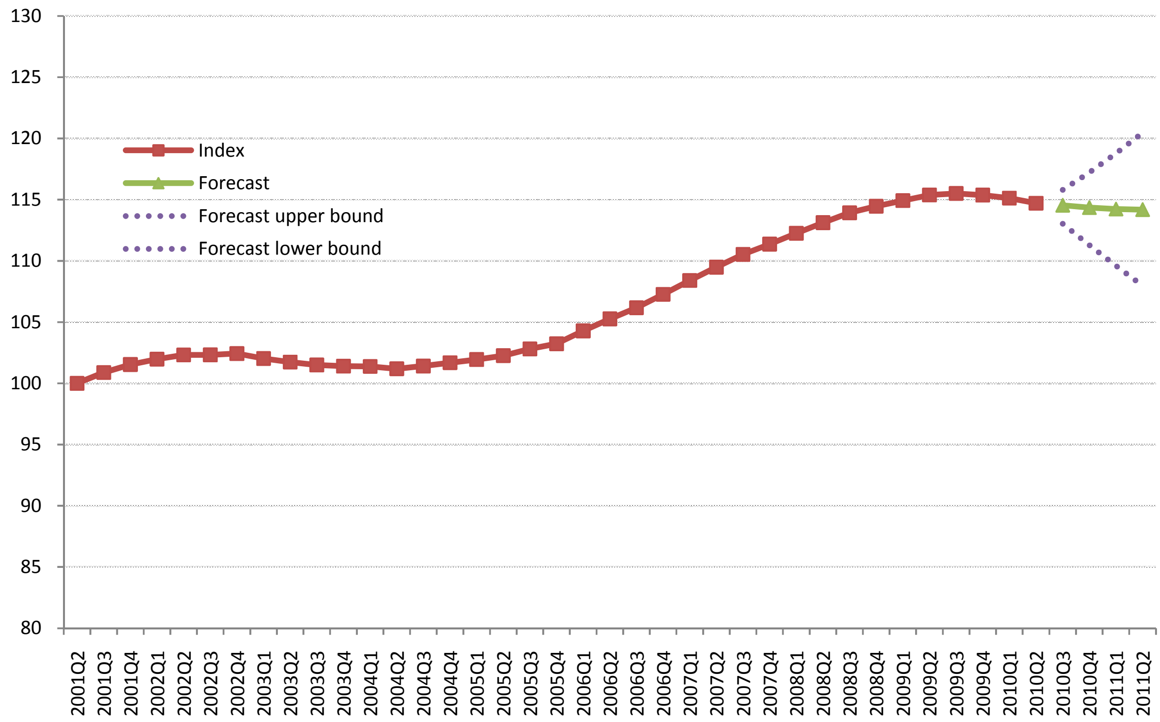

Figure 9 Office Rental Index and its Forecast

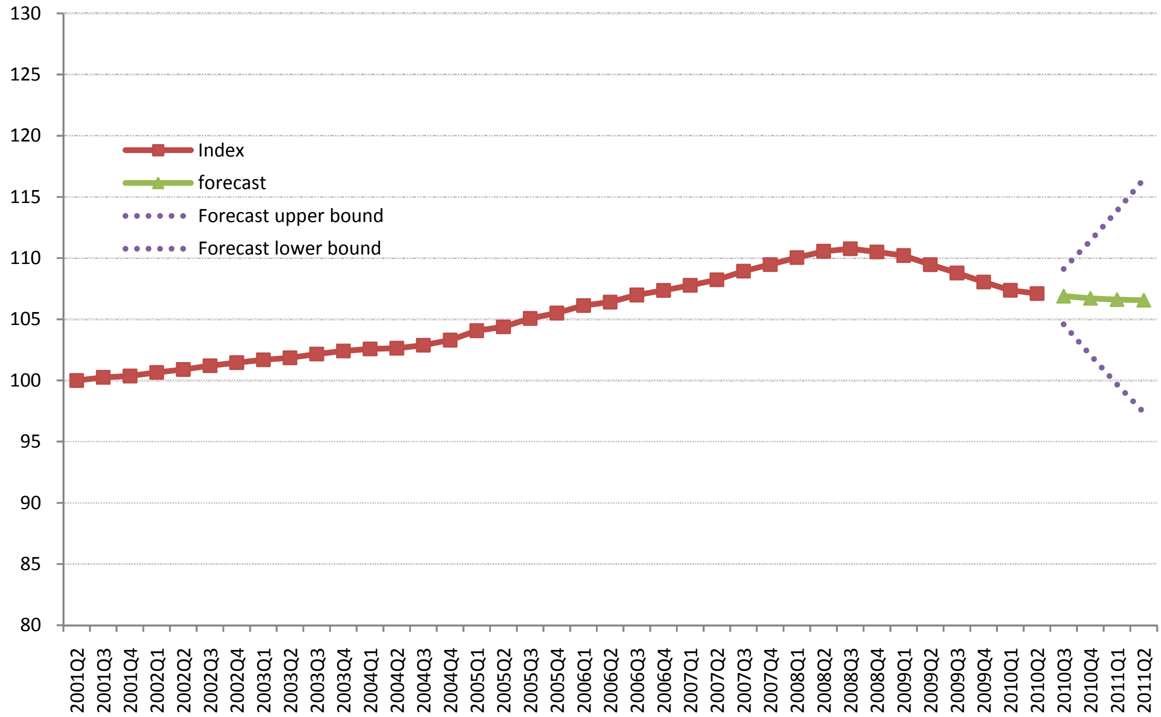

Figure 10 Retail Rental Index and its Forecast

Table 1 Rent Information Availability in Our Sample

Sample	Number of properties	Quarters of rent information available			
		Mean	Min	Median	Max
All property types	9,066	14.54	0	13	41
Apartment	1,974	14.47	0	12	41
Industrial	3,108	15.04	1	13	41
Office	2,498	14.42	1	12	41
Retail	1,486	13.80	1	12	41
Chicago	635	14.64	1	13	41
Atlanta	606	14.85	1	15	41
Washington DC	495	14.25	1	12	41
Dallas	485	14.03	1	12	41
Los Angeles	479	15.19	1	13	41

Note: Data from the National Council of Real Estate investment Fiduciaries (NCREIF). Rents for each property are the actual rents reported from the property management offices that incorporate vacancies and collection losses. They are different from net operating incomes (NOIs) as operating expenses have not been excluded from these numbers.

Table 2: Descriptive Statistics of Log Rent Growth Rate

Sample	Property-quarter	Mean	Median	Std Dev
All property types	82,242	0.011	0.013	0.096
Apartment	20,196	0.008	0.011	0.074
Industrial	27,365	0.012	0.015	0.102
Office	21,530	0.012	0.018	0.106
Retail	13,151	0.008	0.006	0.096
Chicago	22,860	0.007	0.010	0.068
Atlanta	21,816	0.003	0.006	0.069
Washington DC	17,820	0.025	0.023	0.067
Dallas	17,460	0.004	0.007	0.066
Los Angeles	17,244	0.010	0.013	0.071

Note: These are four-quarter (year-over-year) log rent growth rates. Outliers are excluded.

Table 3: Dynamic Panel Data Model Estimates, All Property Types Combined

	GLS Estimates	GMM Estimates
a *100	0.501***	0.675***
	(0.018)	(0.019)
ρ	0.512***	0.384***
	(0.000)	(0.000)
σ_ε *100	2.755***	3.696***
	(0.000)	(0.000)
β *100	-0.170***	-0.199***
	(0.040)	(0.035)
Long term rent growth ($\frac{a}{1-\rho}$) *100	1.027	1.096
Number of properties	9,066	9,066
Property-quarters	82,242	82,242

Note: Standard errors in parentheses. *** for p<0.001, ** for p<0.01, and * for p<0.05. The model is: $r_{it} = \alpha_i + I_t + \beta \cdot age_{it} + u_{it}$; $I_t = a + \rho I_{t-1} + \varepsilon_t$, where r_{it} is the rent growth of property i in quarter t, α_i is the property-specific effect in rent growth (rent growth premium/discount), I_t is the market-wide rent growth (rent growth index), age_{it} is the age of the building (time-varying), and u_{it} and ε_t are disturbances. The distribution of α_i estimates is reported in table 6.

Table 4: Dynamic Panel Data Model Estimates, by Property Type

	Apartment		Industrial		Office		Retail	
	GLS	GMM	GLS	GMM	GLS	GMM	GLS	GMM
a *100	0.113***	0.184***	0.754***	0.925***	0.603***	0.893***	0.462***	0.545***
	(0.023)	(0.026)	(0.030)	(0.031)	(0.041)	(0.046)	(0.051)	(0.054)
ρ	0.745***	0.662***	0.438***	0.328***	0.546***	0.406***	0.369***	0.246***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.005)
σ_ε *100	1.518***	2.168***	3.113***	3.877***	2.475***	3.428***	4.326***	5.210***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β *100	0.171*	0.215**	-0.362***	-0.383***	-0.513***	-0.619***	0.231**	0.260***
	(0.079)	(0.075)	(0.061)	(0.055)	(0.094)	(0.082)	(0.089)	(0.079)
Long term rent growth ($\frac{a}{1-\rho}$) *100	0.444	0.544	1.342	1.376	1.328	1.502	0.733	0.723
Number of properties	1,974	1,974	3,108	3,108	2,498	2,498	1,486	1,486
Property-quarters	20,196	20,196	27,365	27,365	21,530	21,530	13,151	13,151

Note: Standard errors in parentheses. *** for p<0.001, ** for p<0.01, and * for p<0.05. The model is: $r_{it} = \alpha_i + I_t + \beta \cdot age_{it} + u_{it}$; $I_t = a + \rho I_{t-1} + \varepsilon_t$, where r_{it} is the rent growth of property i in quarter t, α_i is the property-specific effect in rent growth (rent growth premium/discount), I_t is the market-wide rent growth (rent growth index), age_{it} is the age of the building (time-varying), and u_{it} and ε_t are disturbances. A separate model is estimated for each property type. The distribution of α_i estimates is reported in table 6.

Table 5: Dynamic Panel Data Model Estimates, Top 5 MSAs

	Chicago		Atlanta		Washington DC		Dallas		Los Angeles	
	GLS	GMM	GLS	GMM	GLS	GMM	GLS	GMM	GLS	GMM
a *100	0.957***	0.782***	0.755***	0.604***	2.297***	1.889***	0.927***	0.717***	0.818***	0.659***
	(0.092)	(0.086)	(0.073)	(0.067)	(0.095)	(0.087)	(0.084)	(0.078)	(0.098)	(0.090)
ρ	0.184***	0.294***	0.171***	0.307***	0.186***	0.318***	0.217***	0.350***	0.197***	0.330***
	0.007	0.007	0.007	0.007	0.008	0.008	0.008	0.008	0.008	0.008
σ_ε *100	0.505***	0.424***	0.448***	0.353***	0.526***	0.437***	0.483***	0.382***	0.538***	0.444***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β *100	-0.562***	-0.506***	-0.882***	-0.853***	-0.501***	-0.468***	-1.041***	-0.967***	-0.102	-0.089
	0.124	0.133	0.106	0.116	0.131	0.142	0.124	0.136	0.138	0.150
Long term rent growth ($\frac{a}{1-\rho}$) *100	1.173	1.108	0.911	0.871	2.823	2.768	1.184	1.103	1.019	0.983
Number of properties	635	635	606	606	495	495	485	485	479	479
Property-quarters	22,860	22,860	21,816	21,816	17,820	17,820	17,460	17,460	17,244	17,244

Note: Standard errors in parentheses. *** for p<0.001, ** for p<0.01, and * for p<0.05. The model is: $r_{it} = \alpha_i + I_t + \beta \cdot age_{it} + u_{it}$; $I_t = a + \rho I_{t-1} + \varepsilon_t$, where r_{it} is the rent growth of property i in quarter t, α_i is the property-specific effect in rent growth (rent growth premium/discount), I_t is the market-wide rent growth (rent growth index), age_{it} is the age of the building (time-varying), and u_{it} and ε_t are disturbances. A separate model is estimated for each MSA although in each MSA all property types are combined. The distribution of α_i estimates is reported in table 6.

Table 6 Rent Growth Premium/Discount Distribution

Sample	GLS Estimates				GMM Estimates			
	Std Dev	5%	Median	95%	Std Dev	5%	Median	95%
All property types	0.032	-0.056	0.001	0.050	0.032	-0.056	0.001	0.050
Apartment	0.025	-0.044	-0.002	0.036	0.025	-0.044	-0.002	0.036
Industrial	0.030	-0.053	0.002	0.047	0.030	-0.053	0.002	0.047
Office	0.037	-0.063	0.003	0.064	0.037	-0.063	0.003	0.064
Retail	0.030	-0.054	0.001	0.045	0.030	-0.054	0.001	0.045
Chicago	0.031	-0.057	0.003	0.046	0.031	-0.057	0.003	0.046
Atlanta	0.032	-0.053	0.000	0.048	0.032	-0.053	0.000	0.048
Washington DC	0.027	-0.037	0.000	0.048	0.027	-0.037	0.000	0.048
Dallas	0.031	-0.057	0.000	0.044	0.031	-0.056	0.000	0.045
Los Angeles	0.029	-0.033	0.015	0.055	0.029	-0.033	0.015	0.055

Note: These are distribution statistics of our estimates of α_i in our model: $r_{it} = \alpha_i + I_t + \beta \cdot age_{it} + u_{it}$; $I_t = a + \rho I_{t-1} + \varepsilon_t$, where α_i represents the rent growth premium/discount of a particular property. We impose the condition that $\sum_i \alpha_i = 0$ so that α_i is relative.

Table 7 Panel Data Regression of Rent Growth on Cap Rate

Dependent variable: Rent Growth Estimate

	(1)	(2)	(3)	(4)
1-quarter lag of cap rate	-0.54***			
	(0.083)			
2-quarter lag of cap rate		-0.49***		
		(0.084)		
3-quarter lag of cap rate			-0.42***	
			(0.086)	
4-quarter lag of cap rate				-0.34***
				(0.087)
Apartment	-0.48**	-0.42*	-0.33	-0.25
	(0.222)	(0.226)	(0.231)	(0.236)
Industrial	0.46**	0.44**	0.42*	0.41*
	(0.207)	(0.212)	(0.218)	(0.224)
Office	0.36*	0.37*	0.37*	0.38*
	(0.206)	(0.211)	(0.218)	(0.224)
Intercept	-0.09	-0.10	-0.11	-0.13
	(0.147)	(0.150)	(0.155)	(0.159)
Observations	144	144	144	144
R-square	0.26	0.22	0.17	0.13
Adj. R-square	0.23	0.20	0.15	0.10

Note: Standard errors in parentheses. *** for p<0.01, ** for p<0.05, and * for p<0.10. These are the results from panel regressions with fixed effects: $r_{i,t+l} = a_i + \gamma c_{i,t} + \varepsilon_{i,t+l}, l = 1, 2, 3, 4$, where $c_{i,t}$ is the cap rate for property type i in quarter t, and $r_{i,t+l}$ is the l-quarter lead of rent growth for the same property type. The panel data has 4 cross sectional dimensions (4 property types) and 36-quarter time series (2001Q3-2010Q2). The retail property type is the omitted group in the regression. The dependent variable is the GLS estimate of rent growth from our dynamic panel data model. The cap rate is the value weighted average cap rate from NCREIF. All variables are standardized before running the regression.

Table 8 Cap Rate Panel Data Regression

Dependent variable: Cap Rate

	(1)	(2)	(3)	(4)	(5)
Rent growth estimate	-0.45***	-0.55***	-0.54***	-0.37***	-0.08*
	(0.065)	(0.063)	(0.054)	(0.064)	(0.048)
Survey commercial mortgage interest rate		0.31***			
		(0.064)			
NCREIF commercial mortgage interest rate			0.45***	0.54***	0.53***
			(0.053)	(0.054)	(0.036)
4-quarter lag of bank tightening commercial real estate credit				0.30***	0.21***
				(0.068)	(0.046)
4-quarter lag of CMBS issuance					-0.55***
					(0.042)
Apartment	-1.00***	-0.82***	-1.00***	-1.01***	-1.02***
	(0.179)	(0.171)	(0.146)	(0.137)	(0.092)
Industrial	0.40**	0.45***	0.43***	0.37***	0.28***
	(0.181)	(0.168)	(0.147)	(0.139)	(0.093)
Office	0.10	0.16	0.14	0.07	-0.05
	(0.181)	(0.169)	(0.147)	(0.139)	(0.094)
Intercept	0.12	0.05	0.11	0.14	0.20***
	(0.127)	(0.120)	(0.104)	(0.098)	(0.066)
Observations	144	144	144	144	144
R-square	0.44	0.52	0.63	0.68	0.85
Adj. R-square	0.42	0.50	0.62	0.66	0.85

Note: Standard errors in parentheses. *** for p<0.01, ** for p<0.05, and * for p<0.10. These are the results from panel regressions with fixed effects: $c_{i,t} = a_i + \gamma r_{i,t} + X_{i,t}\eta + \varepsilon_{i,t}$, where $c_{i,t}$ is the cap rate for property type i in quarter t, $r_{i,t}$ is the rent growth for the same property type, and $X_{i,t}$ are other explanatory variables. The panel data has 4 cross sectional dimensions (4 property types) and 36-quarter time series (2001Q3-2010Q2). The retail property type is the omitted group in the regression. The dependent variable is the value weighted average cap rate from NCREIF. The rent growth estimate is the GLS estimate from our dynamic panel data model. The survey commercial mortgage interest rate is constructed as the 10-year Treasury rate plus the mortgage spread (by property type) from surveys conducted by RealtyRates.com. The NCREIF commercial mortgage interest rate is the average mortgage interest rate of NCREIF properties. The bank tightening commercial real estate credit is the net percentage of survey respondents claiming tightened credit for commercial real estate from the Federal Reserve senior loan officer survey. CMBS issuance is the volume of new CMBS issuance reported by the Commercial Mortgage Securities Association (CMSA). All variables are standardized before running the regression.

Table 9 Commercial Real Estate Price Return Panel Data Regression

Dependent variable: NCREIF price return

	(1)	(2)	(3)
Rent growth estimate	0.36***	0.28***	0.22**
	(0.080)	(0.073)	(0.069)
NCREIF commercial mortgage interest rate		0.42***	0.154
		(0.072)	(0.088)
CMBS issuance relative to commercial real estate sales			0.42***
			(0.090)
Apartment	-0.17	-0.17	-0.16
	(0.222)	(0.199)	(0.185)
Industrial	-0.39*	-0.36*	-0.34
	(0.223)	(0.200)	(0.187)
Office	-0.42*	-0.38*	-0.36
	(0.224)	(0.201)	(0.187)
Intercept	0.24	0.23	0.22
	(0.158)	(0.141)	(0.132)
Observations	144	144	144
R-square	0.14	0.31	0.41
Adj. R-square	0.12	0.29	0.39

Note: Standard errors in parentheses. *** for p<0.01, ** for p<0.05, and * for p<0.10. These are the results from panel regressions with fixed effects: $p_{i,t} = a_i + \gamma r_{i,t} + X_{i,t}\eta + \varepsilon_{i,t}$, where $p_{i,t}$ is the price return for property type i in quarter t, $r_{i,t}$ is the rent growth for the same property type, and $X_{i,t}$ are other explanatory variables. The panel data has 4 cross sectional dimensions (4 property types) and 36-quarter time series (2001Q3-2010Q2). The retail property type is the omitted group in the regression. The dependent variable is the NCREIF price return. The rent growth estimate is the GLS estimate from our dynamic panel data model. All variables are standardized before running the regression.