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A Dynamic Panel Data Model
Estimation**

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KEYWORDS: rental index, cap rate, commercial real estate, dynamic panel data model

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

1. Introduction

The value of commercial real estate is largely determined by its income-generating capacity. Therefore, the risk and returns associated with commercial real estate investment are heavily affected by the cash flow dynamics of commercial properties (Geltner, 1990). In this paper, we develop a new method of constructing a rental index that tracks market-wide rent dynamics. We then use this index to extract information about the rental adjustment process (such as the mean-reversion speed and the volatility of rental growth). In addition, we explore the relation between rent growth and commercial real estate valuation.

Our method is based on an economic model of rental growth decomposition: the growth of an individual property's rental at a specific point can be broken into four components: a time-specific effect representing market-wide rental growth; a property-specific effect due to time-invariant features of the property such as location, amenities, etc.; an effect due to time-varying property characteristics that are identical across cross-sectional units; and finally an individual time-varying effect that represents random shock. This decomposition is carried out in the spirit of price hedonics as outlined in Court (1939) and Griliches (1971). However, our methodology differs from the standard hedonic regression in that we use individual-specific effects instead of characteristic variables to capture cross-sectional variations in rental growth. The benefits of our approach are twofold. First, it does not require detailed data on individual property characteristics, and second, it avoids the omitted variable problem in standard hedonic regressions¹. In addition, we take into consideration the possibility of physical and functional obsolescence in commercial properties. This is of far greater concern in relation to commercial real estate than to residential real estate, and we model its impact through the age effect. This is an improvement over the repeated sales method, which assumes constant property quality over time. This feature also distinguishes our method from the simple (or weighted) average method commonly adopted by practitioners. The identification of our model involves panel data techniques, which are fortunately available with the advancement in panel data econometrics.

¹ Property characteristics are not exhaustive even with the best data collection effort possible.

In addition to the construction of a rental index, we have a second objective in this paper, which is to fit a time series model to the rental index so as to better understand the rental adjustment process. Presumably this could be done in a two-stage approach: in the first stage, a rental index is constructed using a hedonic regression method, or a repeated sales method, or even by using simple averages. In the second stage, a time series model such as an ARMA process is fitted to the rental growth time series estimated from the first stage. Instead of taking the aforementioned two-stage approach, we take an integrated approach in this paper, and estimate both the rental index and its time series model simultaneously. This is done using a dynamic panel data model that we will present in the next section. Besides the obvious benefit of not having to conduct a variance-covariance correction in the second stage of a two-stage approach, our approach benefits from the ability of panel data models to identify model parameters such as increased degrees of freedom and more efficient estimators (Hsiao, 2007). We implement the generalized least squares (GLS) and the generalized method of moments (GMM) estimators proposed by Hsiao and Tahmiscioglu (2008) and Arellano and Bond (1991) in our dynamic panel data model in order to avoid the asymptotic bias of the covariance estimator.

Our model is implemented using a unique proprietary dataset – the actual rentals paid by tenants of 9,066 properties owned by the National Council of Real Estate Investment Fiduciaries (NCREIF) members between the second quarter of 2001 and the second quarter of 2010. Using this rich dataset and a rigorous methodology, we are able to confirm a number of economic intuitions regarding commercial real estate rental market. First of all, rental growth is cyclical and it relates closely to the general business cycles. During the 10-year period between 2001 and 2010, the market-wide rental income derived from the commercial real estate held by NCREIF members had waves of ups and downs. These cyclical behaviors deviate from those generated by a simple stock-flow model (DiPasquale and Wheaton, 1996). They speak to the importance of construction lags and highly price-elastic supply of commercial real estate. Second, the decline in rental growth happened between 2002 and 2003, and later again between 2009 and 2010, and the increase in rental growth happened between 2004 and 2008. Apparently there is generally a one-year lag of the rental growth cycles to the business cycles. This is reasonable due to the long-term leases we usually see in commercial real estate. Third, rental growth is indeed mean-reverting. This rental growth persistency can be caused by certain market frictions such as high transaction cost and lease term inflexibility that prevent investors from leasing commercial space

that has rents that are too low today and leasing it out in the next period. Fourth, the rental accrued from older properties grows at a consistently lower rate, meaning that physical and functional obsolescence is an important part of commercial real estate. From an index construction perspective, controlling for age effects is important to ensure a fair comparison across commercial properties. Finally, the growth of rents follows significantly different patterns across different property types. Findings regarding cross property type differences confirm that commercial real estate market is highly segmented (Archer and Ling, 2012). Different supply and demand elasticity could be the main driver of the different time series pattern in rental growth.

We also discover a number of surprises. For example, the long-term average rental growth rate is significantly smaller than what is usually perceived. Our estimate shows that the nominal long-term average rental growth is slightly over one percent when all property types are combined. Also, we find that the use of the simple average method of constructing the index results in a substantial overestimation of long-term rental growth, and an underestimation of rental growth volatility. Moreover, there are regional variations in rental growth. Among the top 5 MSAs, Washington DC stands out with a significantly higher rental growth in most part of our study period than Chicago, Atlanta, Dallas and Los Angeles, while those four MSAs have very similar rental growth patterns. This is not totally unreasonable given that Washington DC has the US government as its economic base and there are many government leases in the office market, and thus, it is pretty immune from recession².

In addition to creating a rental index and analyzing its time series properties, we examine the relationship among rent growth, cap rate and price returns. As implied by the Gordon (1962) model or the dynamic cap rate model (see, e.g. An and Deng, 2009; Plazzi, Torous and Valkanov, 2010), the growth of income (NOI) among commercial properties should be negatively related to cap rates. However, empirical studies on US commercial real estate cap rates show a weak relationship between cap rates and income growth, leading to speculation about investor irrationality (Hendershott and MacGregor, 2005; Shilling and Sing, 2007). In contrast, we find that a strong negative relationship exists between cap rate and rental growth, and that this

² However, this does not necessarily imply that Washington DC has higher commercial real estate investment return as the high rental growth might have been priced in.

relation is much stronger than that between cap rate and NOI growth. Given that our rental growth measure is an improvement over existing income growth measures (such as the simple average rental or NOI growth) and that typically NOI data contain large amount of noise, this finding leads us to believe that it is important to have accurate measures of commercial real estate income growth to uncover the true economic relationship between cap rate and income growth. One can argue that investors probably have paid more attention to rental growth than to net income (NOI) growth because rental growth is a more reliable indication of long term NOI growth.

Last, we establish a consistent positive empirical relationship between NCREIF price returns and our rental growth estimates. This empirical finding should lead to further inquiries about the theoretical relation between commercial real estate price appreciation and income growth.

Despite the importance of commercial real estate income to the investment community, only limited efforts have been undertaken to model this. Commercial real estate brokers usually use simple averages of asking rent to try to understand local market conditions. Torto-Wheaton Research (TWR) produces an index of asking rents based on new leases using data from CB Commercial leasing brokers (Wheaton, Torto, and Southard, 1997). They adopt a simple regression model similar to a hedonic price regression.³ In contrast to those indices, our rental index measures the actual rental income to investors. This makes it far more relevant to investment performance. The fluctuations in our rental index and in our estimates of rent growth volatility are measures of the cash flow risk associated with commercial real estate investment. We believe our rental index is a good complement to the NCREIF commercial property price index (NPI), and that it will aid significantly in valuation and investment decisions.

Using the same data source, Deng, Fisher, Sanders and Smith (2003) focus on NOI growth and apply the repeated sales index methodology to the construction of an NOI index⁴. Ambrose, Coulson and Yoshida (2013) construct a repeated sales index for residential rental properties. Our average rental growth rate estimate of apartment buildings echoes that of Ambrose, Coulson

³ There are concerns regarding the representation of the TWR database for the rental index due to its reliance on a single brokerage firm.

⁴ See, e.g. Case and Shiller (1987); Englund, Quigley and Redfearn (1999); Clapp (2004); Fisher, Geltner and Webb (1994); Ciochetti, Fisher and Gao (2003), Cho, Kawaguchi and Shilling (2003), and Deng and Quigley (2008) for discussions on the repeated sale index construction for both residential and commercial real estate.

and Yoshida (2013). More recently, Deng, McMillen and Sing (2012, 2013) proposed a matching approach to the construction of residential and commercial indexes for thinly-traded real estate. For future research, our methodology can be applied to the NOI and rental growth of single-family rental properties, and a broader commercial real estate market than the NCREIF market can be further studied using our methodology.

The rest of our paper will proceed as follows: in the next section, we present our model and the logic behind its development. Section 3 comprises a discussion of the data and index estimation results, and Section 4 reports our estimates of the relation among rental growth, cap rate and price return. The paper concludes in Section 5.

2. Rent Growth Model

Consider the growth in the rent of a single property in a commercial real estate market, r_{it} . While the growth rate can have a systematic component that is impacted by market conditions, the growth rate also has an idiosyncratic (property specific) component that is entirely related to the property's own comparative advantages and disadvantages in attracting and retaining renters relative to other properties on the market. Comparative advantages could include a superior location, easier access to the city or motorways, and built-in amenities, which we call hedonics (Griliches, 1971). Comparative disadvantages may include factors such as age as physical and functional obsolescence is common in commercial real estate and older buildings may have lower rental growth potential. It is noteworthy that attributes related to a property's age change with time, thus requiring that the impact of property age on rental growth be separated from other property-specific effects that tend to stay more constant over time. Taking into account these multiple considerations, we decompose the rent growth of a particular property at a particular time into the following:

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

where α_i represents the time-invariant property-specific effect of the property's unique comparative advantage, I_t represents the time-varying market-wide rental growth rate, $\beta \cdot \text{age}_{it}$ represents the aging effect, and $u_{i,t}$ is the error term that represents possible 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 or discount.

Consider further the market-wide rent growth rate, I_t . From the perspective of space market equilibrium, supply-demand adjustments will cause the market (asking) rent to fluctuate around a long-term mean: if rent in a certain market is too high, developers and investors will create new spaces to try to take advantage of the high rent but then new supply will eventually bring rent down. If we assume the random arrival of new leases in a market, the average actual rent should have a high correlation with the asking rent⁵, and, thus, tend to also fluctuate around a long-term mean. Further, due to investors' inability to quickly arbitrage away rental growth opportunities due to high transaction cost, the rental adjustment process is sluggish. Therefore, we expect rental growth to exhibit mean-reversion. In fact, Wheaton and Torto (1994) and Hendershott and MacGregor (2005) demonstrate that the real rents of office and retail properties in the US and UK are mean- or trend- reverting. Geltner and Mei (1995) demonstrated further that the NOI of NCREIF properties is also significantly autocorrelated. Therefore, we model I_t with the following autoregressive process:

$$I_t = a + \rho I_{t-1} + \varepsilon_t, 0 < \rho < 1. \quad (2)$$

The standard deviation of ε_t , σ_ε , is the volatility of rental growth.

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

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

This is a dynamic panel data model with individual specific effect α_i^* and time specific effect ε_t . A covariance estimator of this model will be asymptotically biased, necessitating the application of the generalized least squares (GLS) and the generalized method of moments (Hsiao and Tahmiscioglu, 2008). The estimation procedure is discussed in greater detail in the appendix.

3. Model Estimates and Rental Index

⁵ Data from REIS actually show that effective rent and asking rent are highly correlated.

3.1. Data

The NCREIF started to collect detailed rental information (base rent, contingent income, reimbursement income and other income) in 2000, and these data are used to calculate the NOI adopted in the NCREIF property index. Accessing the NCREIF database, we obtained longitudinal rental data of nearly 10,000 commercial properties located all across the nation. Note that these data are different from the NOIs reported by the NCREIF and used for its NOI indices. Our data are different also in that we adopt the never-before used rental income derived before the deduction of operating expenses to construct an index of changes in rental rates.

The rental data adopted spans 41 quarters, starting from Q2 of 2000, and ending in Q2 of 2010. However, the individual rental rates available often do not span the full 41 quarters, with different properties having rates available from different quarters. In Table 1, we provide a summary of the availability of the rent information in our sample. We focus mainly on the four major property types: apartments, industrial properties, offices, and retail spaces. After excluding other property types, a total of 9,066 properties remain, with an average of 14.5 quarters worth of rent information on each property. We also break down the rent information availability by property type. The average length of time for which rental information is available for apartments, industrial properties, offices and retail spaces 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. Table 1 provides comprehensive information on the number of properties in our sample, and the availability of the rental information associated with them.

Based on the rental information, we calculate the 4-quarter log rental growth (year-over-year) of each property in each quarter.⁶ We find some unreasonably high or low rental growth in our sample. That could be due to a number of reasons: 1) substantial capital expenditure that causes abnormal rent growth; 2) property addition/expansion which causes extraordinary rent growth; 3) unusual accounting adjustments that reverse previous accruals or reflect one-time events such as a lease buyout by a tenant, and 4) data errors. Irregular rental growth caused by any of these

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

reasons is not a reflection of market rental growth. Therefore, we exclude apparent outliers in our sample.

We report summary statistics of rental growth in Table 2. These data exclude outliers and span 82,242 property-quarters. On average, these properties enjoyed a growth in rent of 1.1 percent per year in the 10 years between 2001 and 2010. The standard deviation of the growth was 9.6%. Industrial and office properties demonstrated higher than average rental growths, while retail properties and apartments performed at lower than average rates. Apartments had the lowest rent growth dispersion, while office properties had the highest.

The average rent growth varies substantially across MSAs. From Table 2, we see that Washington DC enjoyed an average rental growth rate of 2.5% - the highest increase of our study period. In contrast, Atlanta and Dallas both demonstrated low average rental growths of 0.3% and 0.4%, respectively. The dispersions of rent growth did not differ significantly amongst the 5 MSAs.

3.2. Rent Growth Estimate and Rental Index

In Figure 1, we present our rent growth estimates for each quarter in our 10-year period, together with the NPI price return and total return for those quarters. We calculated our rental index based on these estimates and present it with the NPI price index in Figure 2.

In both figures, we put the GLS estimates and the GMM estimates side by side. Theoretically, the GLS estimator has smaller bias (Hsiao and Tahmiscioglu, 2008). But we can see they are really close in this context.

We made a number of interesting observations regarding the behavior of rent. First, rent growth is cyclical. In the nine years between 2001 and 2010, the markets appear to have experienced a full growth cycle as evidenced by positive rental growth in the early 2000s, followed by a downturn between 2003-2003, followed again by strong rental growth in the years between 2005 and 2008 in the US commercial real estate sector. Rental rates started to fall again from the third quarter of 2009, in the aftermath of the global financial crisis. Certainly, the cyclicity of rental growth is intuitive: rental income of commercial real estate such as offices, retail spaces and industrial spaces is highly dependent on employment, consumption and production, and, thus, the

general business cycles have a strong impact on rental growth. Further, the difficulty to demolish spaces and construction lags can keep the supply-demand imbalances to remain for relatively long time, and, thus keep prolonged ups and downs in rental growth.

Second, rental growth tends to lag behind economic recessions. For example, although the dot com bubble burst in 2001, and was quickly followed by a serious economic recession, we begin to see negative rental growth rates only in the second quarter of 2002. More recently, the growth in rental slowed down significantly in the last quarter of 2008, but rental growth only turned negative in the third quarter of 2009. The timing of the downturn lagged behind the mortgage market crisis, the financial crisis and the subsequent economic recession. However, such sluggishness is to be expected, given that commercial real estate leases, especially office, retail and industrial leases tend to stipulate relatively long term periods, and rate adjustments tend thus to be slow. Nonetheless, from Figure 2, we can see that during the recent recession, the rent decline lagged behind the drop in property values by about a year. This pattern suggests that at the start of the recent crisis the commercial real estate market downturn was driven originally by the collapse of the real estate capital market, rather than the space market imbalance. This is supported by anecdotal evidence which shows that the slashing of commercial real estate value in the recent recession was driven largely by the increase in cap rate. Of course, when we propagated further into the recession, we see significant rental decline and that decline further drove value drop.

Finally, we observe from Figure 2 that rental rates are much more stable than commercial real estate prices. Between 2001 and 2010, the NPI grew from 95 to almost 145, from trough to peak. In contrast, the rental index only rose from 100 to about 112. This suggests that the discount rate was a more significant driver of commercial real estate value than income growth during this time period.

Next, we go behind the scene of the aforementioned figures to look more closely at the estimates of our model parameters. 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 α , ρ , β and σ_ε are significant at the 99.9% level. Notice that β is significant and negative, confirming our speculation that older properties tend to have smaller rental growth potential. This raises the question of a possible property quality bias (effectively an age-bias) in

the practice of commercial real estate brokers. Such brokers usually calculate rental growth or average rent by taking the simple average of the current stock of properties. In order to show the difference, we plot both our age-adjusted rental index and a simple average index on the same chart (Figure 3). Given that average property age increases over time, we can see that the simple average index under-estimates rental growth in the later years of our sample period.

Turning to the time series properties of the rental index, as expected, ρ is less than 1, indicating that market-wide rent growth is indeed mean-reverting. We calculate the long-term average/equilibrium rent growth based on our estimates of α 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. These average long term rental growth rate estimates are surprisingly low at first glance, especially if you remember that we usually teach our students to assume a rental growth of 3 percent per year in pro forma analysis. However, the 1% rental growth estimate is consistent with that found by Ambrose, Coulson and Yoshida (2013), who looked at the rental growth rate of single-family rental properties in 11 US metro areas using a repeated sales method.

The conventional approach to addressing the time series properties of rental growth or price returns would involve a two-stage process. First, one estimates the rental or price index using a particular methodology (hedonic regression, repeated sales method, or simple averages). One then fits an ARMA process to the estimated rental index or price index. We compare our panel data model estimates formed using a simultaneous one-stage estimation with that formed using a two-stage process of estimation. Table 4 presents the ρ and σ_ε estimates, as well as our calculation of the long-term average rental growth based on these two parameters. In comparing the point estimates of the mean-reversion parameter and the long-term average rental growth parameter, we can see that our panel data method provides significantly smaller estimates of ρ and α . The long term average rental growth estimated from AR1 is many times higher than that estimated using our method.

Certainly, in addition to the mean, we care also about the volatility of the rental index, which is a risk measure of rental income. It is actually a more accurate risk measure than the more typically used standard deviation of rental growth. This is because the standard deviation of the cross sectional time series rent growth contains the cross sectional variation that is diversifiable in a

portfolio⁷. The estimated volatility of the rent growth is high, and calculated at 2.8% from the GLS estimate, and 3.7% from the GMM estimate. By contrast, the volatility of rental growth estimated using an AR1 is only about 0.5%. Thus we see that the two-stage method can significantly over-estimate the long-term mean of rental growth, while significantly under-estimating the risk of rental income.

In Table 5, we present our estimation results for separate property types. The results show that the commercial real estate market is highly segmented by property type. We see that the growth in the rent of all property types is mean-reverting 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 the GLS estimate, and 0.75 based on the GMM estimate), followed by industrial properties (0.56 based on the GLS, 0.67 based on GMM), office spaces (0.45 based on the GLS, 0.59 based on GMM), and apartments (0.25 based on GLS, 0.34 based on GMM). This pattern seems to be counterintuitive, given that the supply of apartment spaces is usually more elastic than that of retail, industrial and office spaces. However, it could be the low demand elasticity that makes the adjustment of apartment rent growth slower. It could also be that apartment rental rates can respond much more quickly to new market information and diverge more greatly from previous levels because apartment leases are much shorter than that of other property types.

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 these four property types following the aforementioned order. Therefore, the long-term average rent growth is substantially different for each of the 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%. The estimated volatilities are significantly smaller than the standard deviations of the rent growths reported in Table 2 (7.4%, 10.2%, 10.6%, and 9.6%). From the risk-return perspective,

⁷ Neither does the standard deviation of a time series rental index serve as a good risk measure because it does not take into consideration the potential autocorrelation in the index. 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.

retail spaces are the worst performing as they demonstrate only moderate long-term average rental growth rates, while boasting the highest levels of growth rate volatility.

Looking at the age effect, it is clear that industrial and office properties continue to suffer the ravages of time, with older properties demonstrating significantly lower rental growth rates. Interestingly however, apartment and retail properties do not demonstrate such a pattern, possibly because apartment complexes and shopping centers only become mature after a few years when they start to attract a stable stream of tenants. Therefore, older apartment complexes and shopping centers tend to see higher rental growth.

To further demonstrate the differences in rental growth across property types, we plot the rental indices of the four property types in Figures 4 and 5. The differences are prominent. During the 2002-2003 downturn, apartment rents were the first to fall, showing a decline as early as in the fourth quarter of 2001. Office rents started to fall only in the first quarter of 2003. This is possibly due to the constraints imposed by longer lease terms as discussed earlier as office leases are usually of 3 to 5 year duration, while apartment leases are usually shorter. Apartment rental rates respond to the economic recession much more quickly than office rents. Industrial rents have seen persistent growth in the last decade, and suffered only a slight decline during the recent crisis. Office properties accumulated the highest rental growth in the entire 10-year period.

The traditional view about the real estate market is that it is highly localized (Archer and Ling, 2012). However, the recent decades have witness the development of a more unified capital market that has strong impact on commercial real estate development and investment. Moreover, real estate management has become more standardized and cross-region property management is now very common with the big management companies for institutional investors. Therefore, it is interesting to see whether there is still significant geographic variation in the commercial real estate rental market and how the geographic variation has changes over time.

In Table 6, we present our model estimates for the top 5 MSAs: Chicago, Atlanta, Washington DC, Dallas, and Los Angeles. All model parameters are significant for all MSAs at the 99.9% significance level, except the age effect for Los Angeles. Interestingly, in each of the aforementioned markets, the mean-reversion speeds of rental growth are similar for all five MSAs. The volatilities in rental growth are also similar across the five MSAs. Chicago, Atlanta,

Dallas, and Los Angeles are close in terms of long term average log rent growth, posting rates of between 0.91 and 1.18% per year based on the GLS estimates, and between 0.87 and 1.11% per year based on GMM estimates. These findings tend to suggest that in the recent decade geographic variation in the commercial real estate rental market has diminished, at least for those properties held by institutional investors. However, we notice that Washington DC really stands out as the best performing rental market, with a long-term average log rent growth of 2.8% per year. This is a huge difference between Washington DC and the other four MSAs. In Figures 6 and 7, we plot the rental index of the top five MSAs based on the aforementioned rent growth estimates. Again, we see that Washington DC stands out for its extraordinary rental growth during our study period when all other MSAs saw some significant declines during certain periods. The superior performance of the Washing DC market is not totally unreasonable: with the US government as its economic base and many government leases, it is pretty immune from recession. Then the question is why the spatial arbitrage opportunities are not taken away by investors and developers. We will leave further inquiries of this issue to future studies.

Finally in this section, we report the distribution of our rent growth premium/discount estimates of individual properties in Table 7. We see that some properties have significantly higher/lower rent growth than the population at large. For example, office properties at the 95th percentile showed 6.4% higher rental growth per annum than those in the 50th percentile. In contrast, office buildings at the 5th percentile showed 6.3% per annum lower rental growth than average. It would be worth investigating in future studies the causes of the rent premiums and discounts, looking perhaps more closely at property characteristics such as location, ease of access, size, walkability, greenness, etc. In terms of cross-property type comparisons, office properties have the highest dispersion in rent premiums, while apartment buildings have the lowest, making their rental rates far more homogeneous than that of office properties.

4. Rent Growth, Cap Rate and Price Return

In theory, income growth has a negative relationship with cap rate. In a static Gordon (1962) model, cap rate is the difference between the required return (discount rate) and the expected income growth, i.e.,

$$c = R - g. \quad (17)$$

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 expected income growth in a dynamic setting:

$$c_t = E_t \sum_{j=1}^{\infty} \rho^{j-1} (r_{t+j} - g_{t+j}) - \frac{k}{1-\rho}, \quad (18)$$

where c_t is the log cap rate at time t , r_{t+j} and g_{t+j} are log return and log income growth respectively, at time $t + j$, and ρ and k are constants. E_t denotes expectation at time t .

However, the existing literature on cap rate has failed to empirically confirm the negative relation between cap rate and income growth. Earlier studies such as that by Hendershott and Turner (1996) and Chichernea, Miller, Fisher, Sklarz and White (2008) discuss rent growth as a determinant of cap rate, but they do not include rent growth in their empirical analysis. Recent studies try to estimate the relationship between commercial real estate cap rates, return rates, and income growth, but these authors have found the relationship between cap rate and rent/NOI growth to be weak, if at all existent. For example, Shilling and Sing (2007) estimated a set of VAR models using the Korpacz survey cap rate, NCREIF rate of return, and a proxy of net rent growth derived from NCREIF property income growth. The authors found virtually no statistically significant relationship between cap rate and net rent growth. Clayton, Ling and Naranjo (2009) then looked at the RERC survey cap rate, expected return, and expected rent growth. Using OLS regressions and vector error correction models, they found a weak relationship between cap rates and rental growth. Plazzi, Torous and Valkanov (2010) in turn used GRA data on average cap rates and rental growth rates, as well as REITs return data and found that a significant relationship was found between rent growth and cap rate only for office properties.

Having already estimated rent growth based on NCREIF data, we collect further data on NCREIF cap and return rates, and use this information to examine the relation between rent growth and cap rates and returns.

Following Plazzi, Torous and Valkanov (2010), we first run the following predictive regressions

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

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

We report our first set of results in Panel A of Table 8. Here the dependent variable is our log rent growth estimate, and the explanatory variable is the log value-weighted transaction cap rate of NCREIF properties. According to Hsiao and Tahmiscioglu (2008), the GLS estimator has smaller bias and mean square error than the GMM estimator so we focus on the GLS estimator of rent growth hereinafter. Because of limitations in our data, we have combined all property types in our analysis⁸. We see that the lagged cap rate has a strong negative relation with our rent growth estimate, suggesting that cap rates are actually informative of future rent growth. We also see that the magnitude of the coefficients degenerate as cap rates go further into the past. This is completely consistent with the theoretical relation in equation (18). In panel B of Table 8, we report our results based on NCREIF current value cap rates instead of on the transaction cap rate. The value-weighted current value cap rate is appraisal-based, and so faces the problem of appraisal smoothing. However, it is valuable in that it represents the valuation information of an important group of commercial real estate market participants, namely appraisers. The benefit of using the current value cap rates in our analysis is that it allows us to break the information down according to property type, so that we can run a panel data regression. The results in Panel B of Table 8 are highly consistent with those in Panel A. The lagged cap rate demonstrates a strong negative relationship with our rent growth estimate, and the magnitude of the coefficients degenerate as the cap rate goes further into the past.

Notice that in the cap rate model, g is the expected growth in income, which is rent minus operating expenses. Therefore, rent growth is only a proxy of income growth, as operating expenses can vary over time and their variation may not synchronize with that of rent. For this reason, we re-run the predictive regression (equation 19) using NOI growth instead of rent growth. We report our results in Table 9. Again, Panel A shows the results based on the

⁸ We conduct standardization of the variables including de-meaning and standard deviation adjustment.

transaction cap rate for all property types combined, while Panel B shows the results based on current value cap rates in a panel data regression. We see that the lagged cap rate has a significant negative relation with NOI growth. However, when we compare the results in Table 8 and Table 9, we see, interestingly, that the relation between cap rate and NOI growth is not as strong as the relation between cap rate and rent growth. This is counterintuitive as NOI should be a more precise measure of the net cash flow to investors than rent, and thus NOI growth should be more closely related to cap rate. A possible explanation for the discrepancy is that on the time series dimension, variation in the growth in operating expenses is under-estimated by investors and appraisers. Alternatively, investors might have found that historical rent growth is a better proxy for what they think future NOI growth will be where in the long run expenses tend to be a fixed percent of rent. NOI data usually contains significant noise due to short run variations in expenses and our rental growth estimates are improved measures of the true market-level rental growth (e.g., over the simple average measure). Therefore, it is important for us to use accurate data in order to discover the true economic relation between cap rate and income growth.

Economic theory such as the Gordon growth model and the dynamic cap rate model states clearly the relation between cap rate and income growth/required rate of return. And there is a clear theoretical relation between price and income growth. However, it is not clear how *price return* and income growth are (should be) related⁹. Therefore, using the *ex post* price return, we try to explore the relation between rental growth and NCREIF price returns here.

We run the following regression:

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

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 $X_{i,t}$ represents other explanatory variables.

We present the panel data regression results in Table 10. Interestingly, we find a consistent positive relation between NCREIF price return and our rent growth estimate in various specifications. Certainly we are only establishing an empirical relationship here and we leave further inquiries of the theoretical relation between price return and rental growth for future

⁹ Higher income growth can lead to higher *price* but not necessarily higher *price return*.

studies. However, the current exercise does suggest that rental growth could be a predictor of price return for commercial real estate. We also notice that when we use the risk free rate instead of the mortgage interest rate, we obtain a better fitting model. This is possibly due to the endogeneity of the mortgage interest rate, as the time varying risk premium is a determinant of both our LHS and RHS. In other words, the risk-free rate is an exogenous variable that better explains the commercial real estate price returns than the mortgage interest rate.

5. Conclusion

A significant portion of the return from commercial real estate investment comes from rental income. Naturally then, the value of a piece of commercial real estate is largely determined by its capacity to generate income. Therefore, rental growth is a critical variable closely watched by brokers, developers, and investors alike, along with changes in vacancy and net absorption. Despite its importance to the investment community, limited efforts have been undertaken to model commercial real estate rental income. In this paper, we construct a 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 rent growth, and to mitigate the omitted variables problem in a standard hedonic regression approach. We also consider physical and functional obsolescence in commercial properties and model it through the age effect in our panel data model. This addresses a critical issue in the repeated sales methodology, which is that property quality does not remain constant over time, which is an assumption in regressions involving repeated sales. Using a panel data model, we were also able to estimate the economic process that governs the time series dynamics of market-wide rent growth while also estimating the rental index. This estimator is more consistent than that obtained from a two-stage approach.

We were able to implement our model and estimate the rental index by using data on the actual rent received from commercial properties held by NCREIF members. Based on our index, we find that rental growth is cyclical but generally lags behind broader economic growth. In addition, commercial real estate rents are much more stable than their prices. Our estimates show that older properties tend to have lower rental growth rates, suggesting that physical and functional

obsolescence is an important issue in commercial real estate. Market-wide rental growth is mean-reverting and the long-term average rental growth is significantly lower than what is usually perceived. We also provide a new measure of rental income risk, which is the volatility of the rental index we estimate from our model. We demonstrate that the simple average method of constructing a rental index can lead to age-bias, and that a two-stage estimation approach on the time series properties of rental growth can significantly over-state average rental growth and under-estimate rental growth volatility.

Expected income growth is an important determinant of cap rate in theory. However, the existing literature shows that commercial real estate cap rates in US are poorly related with income growth, leading to speculation that investors are irrational. Our findings differ from this trend in that we show a strong negative relation between cap rate and our rental growth estimate. We show further that the relationship between rental growth and cap rates are stronger than that between NOI growth and cap rates. These findings suggest that investors and appraisers rely more heavily on rental growth in forming their valuations (cap rates) most likely because rent growth is a better indication of long term NOI growth because expenses are noisy in the short run. Finally, we establish a consistent positive empirical relationship between NCREIF price returns and our rental growth estimates.

We believe that our rental index is a good complement to the NCREIF commercial property price index (NPI) in helping the investment community assess the risks and returns of commercial real estate investments. Future research can apply our methodology to a broader spectrum of commercial properties, e.g. the properties covered by CoStar. Our methodology can also be applied to construct an NOI index and a rental index for single-family residential rental properties.

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Appendix: Estimation Procedure for the Rent Growth Model

Taking first difference of (3), we have

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

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

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

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 $\Delta r_{it}^* = \Delta \xi_{it}^*$ as in Hsiao and Tahmiscioglu (2008), we have the following two estimators:

The Generalized Least Squares Estimator (GLS)

Let $\Delta r_{0\%}^* = (\Delta r_{i2}^*, \dots, \Delta r_{iT}^*)$, $\Delta r_{0\%}^{*-1} = (0, \Delta r_{i2}^*, \dots, \Delta r_{iT-1}^*)$ and $\Delta \xi_{0\%}^* = (\Delta \xi_{i2}^*, \dots, \Delta \xi_{iT}^*)$.

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

$$\Delta r_{0\%}^* = \begin{pmatrix} \Delta r_{0\%}^* \\ \mathbf{M} \\ \Delta r_{0\%}^* \end{pmatrix} = \begin{pmatrix} \Delta r_{0\%}^{*-1} \\ \mathbf{M} \\ \Delta r_{0\%}^{*-1} \end{pmatrix} \rho + \begin{pmatrix} \Delta \xi_{0\%}^* \\ \mathbf{M} \\ \Delta \xi_{0\%}^* \end{pmatrix} = \Delta r_{0\%}^* \rho + \Delta \xi_{0\%}^* \quad (6)$$

It is known that

$$E(\Delta \xi_{0\%}^*) = 0, \quad E(\Delta \xi_{0\%}^* \Delta \xi_{0\%}^{*'}) = \sigma_\xi^2 \left(1 - \frac{1}{N}\right) A, \quad E(\Delta \xi_{0\%}^* \Delta \xi_{0\%}^{*'}) = \sigma_\xi^2 \left(-\frac{1}{N}\right) A, \quad i \neq j$$

Therefore,

$$E(\Delta \xi_{0\%}^* \Delta \xi_{0\%}^{*'}) = \sigma_\xi^2 (Q \otimes A) = \sigma_\xi^2 \Omega$$

where

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

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

$$Q = I_N - \frac{1}{N} \mathbf{e}_N \mathbf{e}_N', \quad \mathbf{e}_N \text{ is an } N \times 1 \text{ vector of ones.}$$

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

$$\begin{aligned} \hat{\rho}_{GLS} &= [\Delta r_{\sigma_h}^{*'} \Omega^- \Delta r_{\sigma_h}^{*'}]^{-1} [\Delta r_{\sigma_h}^{*'} \Omega^- \Delta r_{\sigma_h}^{*'}] \\ &= \left[\sum_{i=1}^N \Delta r_{\sigma_0}^{*'} A^{-1} \Delta r_{\sigma_0}^{*'} \right]^{-1} \left[\sum_{i=1}^N \Delta r_{\sigma_0}^{*'} A^{-1} \Delta r_{\sigma_0}^{*'} \right] \end{aligned} \quad (7)$$

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

The Generalized Method of Moments (GMM) estimator

Equation (5) satisfies the moments conditions

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

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

$$\Delta r_{\sigma_0} = \Delta r_{\sigma_0} \rho + \Delta \xi_{\sigma_0}^*, \quad i = 1, \dots, N \quad (9)$$

where

$$\Delta \rho_{0\%}^* = (\Delta r_{i3}^*, \dots, \Delta r_{iT}^*)', \Delta \rho_{0\%}^{*1} = (\Delta r_{i2}^*, \dots, \Delta r_{i,T-1}^*)', \Delta \xi_{0\%}^* = (\Delta \xi_{i3}^*, \dots, \Delta \xi_{iT}^*)'.$$

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

$$E(W_i \Delta \xi_{0\%}^*) = 0, \tag{10}$$

where

$$W_i = \begin{pmatrix} q_{i3} & 0 & L & 0 \\ 0 & 0 & & 0 \\ 0 & q_{i4} & & \\ M & M & O & \\ 0 & 0 & & q_{iT} \end{pmatrix}, i = 1, \dots, N; q_{it} = (r_{i1}, r_{i2}, \dots, r_{i,t-2})', t = 3, \dots, T.$$

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

$$\rho_{GMM} = \left\{ \left[\frac{1}{N} \sum_{i=1}^N \Delta \rho_{0\%}^* W_i' \right] \Psi \left[\frac{1}{N} \sum_{i=1}^N W_i \Delta \rho_{0\%}^* \right] \right\}^{-1} \left\{ \left[\frac{1}{N} \sum_{i=1}^N \Delta \rho_{0\%}^* W_i' \right] \Psi \left[\frac{1}{N} \sum_{i=1}^N W_i \Delta \rho_{0\%}^* \right] \right\} \tag{11}$$

where $\Psi = \hat{\sigma}_\xi^2 \left[\sum_{i=1}^N W_i \mathcal{A} W_i' \right]$, $\mathcal{A}_{(T-2) \times (T-2)} = \begin{pmatrix} 2 & -1 & 0 & 0 & \dots & 0 \\ -1 & 2 & -1 & \dots & \dots & \dots \\ 0 & -1 & 2 & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & 2 & -1 \\ 0 & \dots & \dots & \dots & -1 & 2 \end{pmatrix}$,

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

Estimation of a , 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 a by rearranging equation (3):

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

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 $(\delta_{it}) = E[(1 - \rho)\alpha_i + \varepsilon_t + u_{i,t} - \rho u_{i,t-1}] = 0$, 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:

$$\begin{aligned} \frac{1}{N} \sum_{i=1}^N r_{it} &= \rho \frac{1}{N} \sum_{i=1}^N r_{i,t-1} + a + \frac{1}{N} \sum_{i=1}^N \alpha_i + \varepsilon_t + \frac{1}{N} \sum_{i=1}^N \xi_{it} + \frac{1}{N} \sum_{i=1}^N (age_{it} - \hat{\rho} \cdot age_{i,t-1}) = \\ &\rho \frac{1}{N} \sum_{i=1}^N r_{i,t-1} + a + \varepsilon_t + \frac{1}{N} \sum_{i=1}^N \xi_{it} + \frac{1}{N} \sum_{i=1}^N (age_{it} - \hat{\rho} \cdot age_{i,t-1}), \quad t = 2, \dots, T, \end{aligned} \quad (14)$$

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 \mathfrak{H}_{ξ}^2 has been calculated in the estimation of ρ , $\mathfrak{H}_{\varepsilon}^2$ can be estimated as:

$$\mathfrak{H}_{\varepsilon}^2 = \overline{Var(\varepsilon_i + \frac{1}{N} \sum_{i=1}^N \xi_{it})} - \frac{1}{N} \mathfrak{H}_{\xi}^2. \quad (16)$$

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

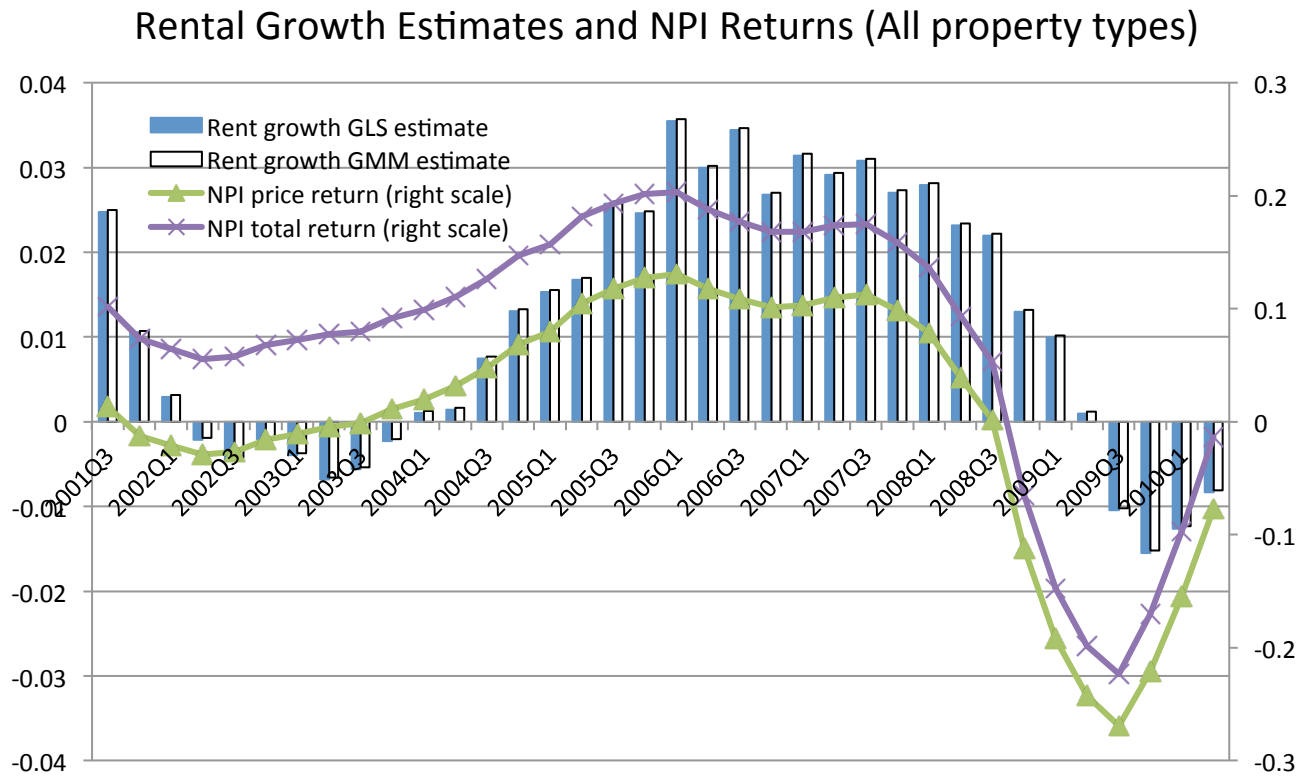


Figure 1 Rental Growth Estimates and NPI Returns (All property types combined)

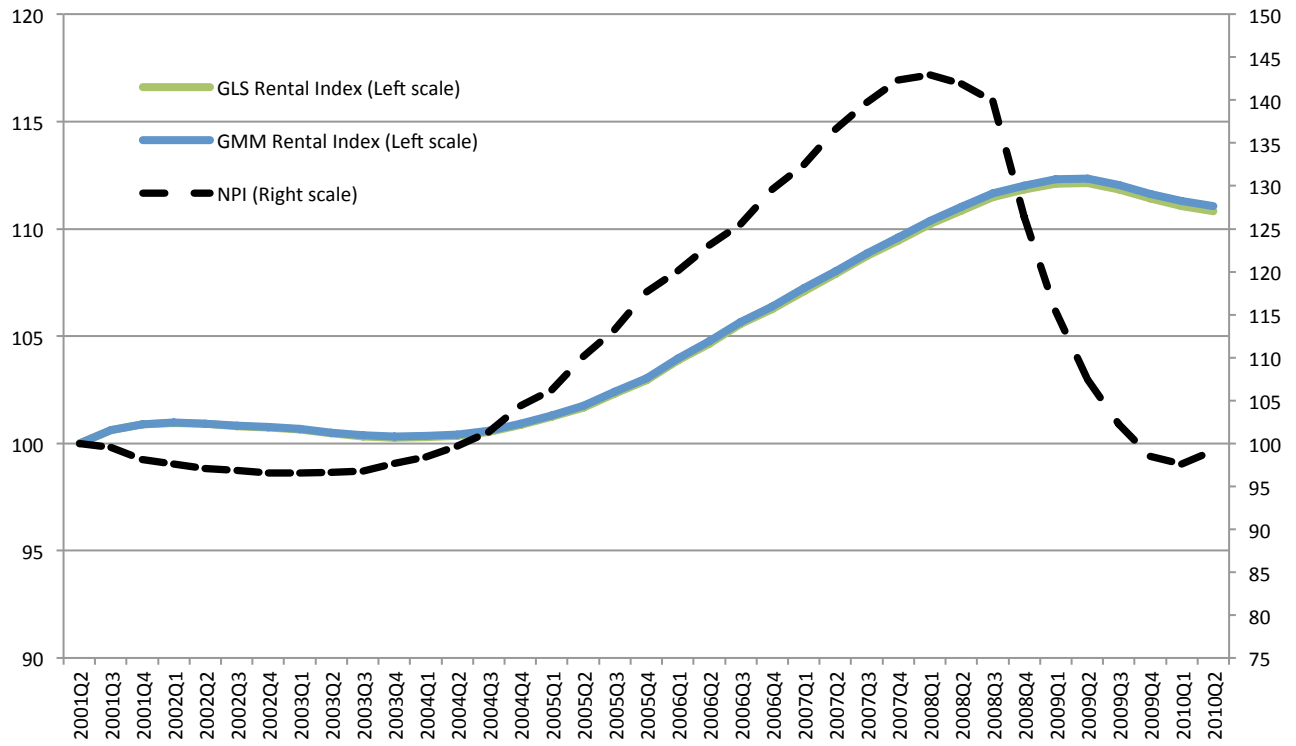


Figure 2 Rental Index and NPI (All Property Types Combined)

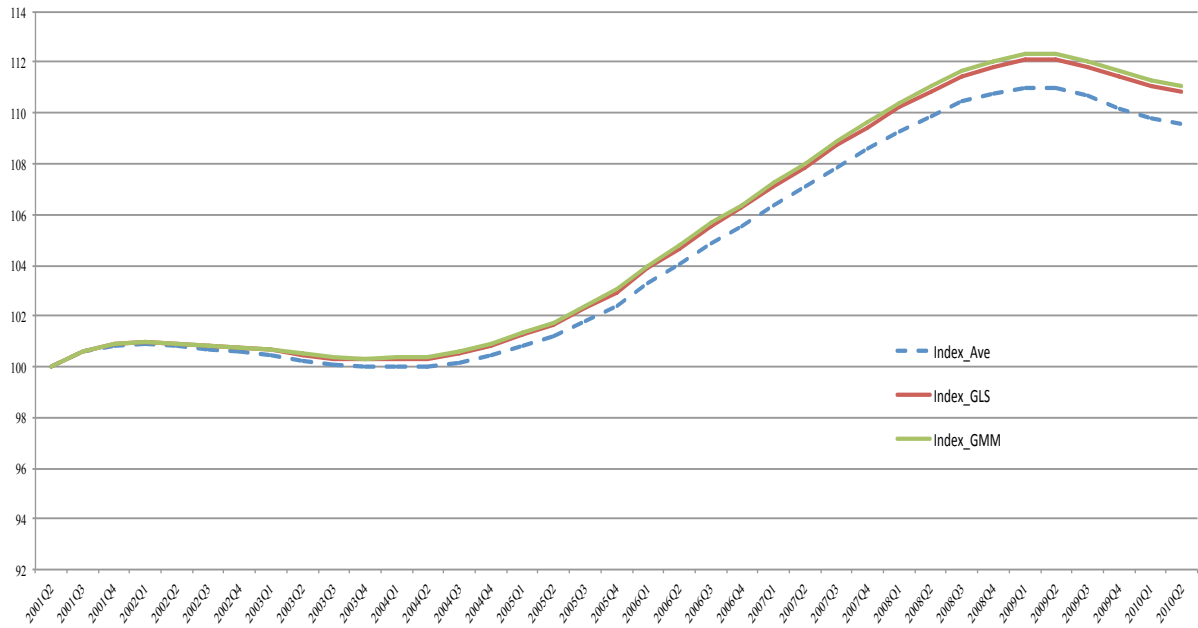


Figure 3: Comparison of the Rental Indexes Constructed using the Simple Average Method and Our Panel Data Model

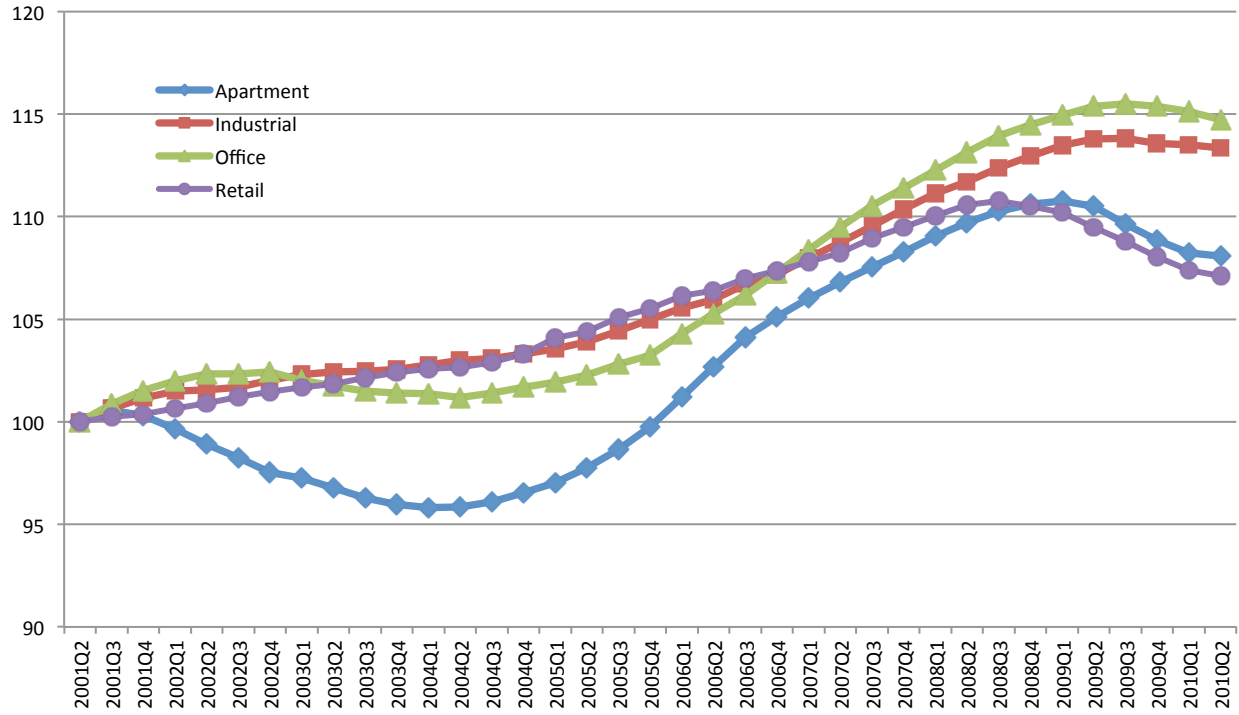


Figure 4 Rental Index by Property Type (GLS Estimates)

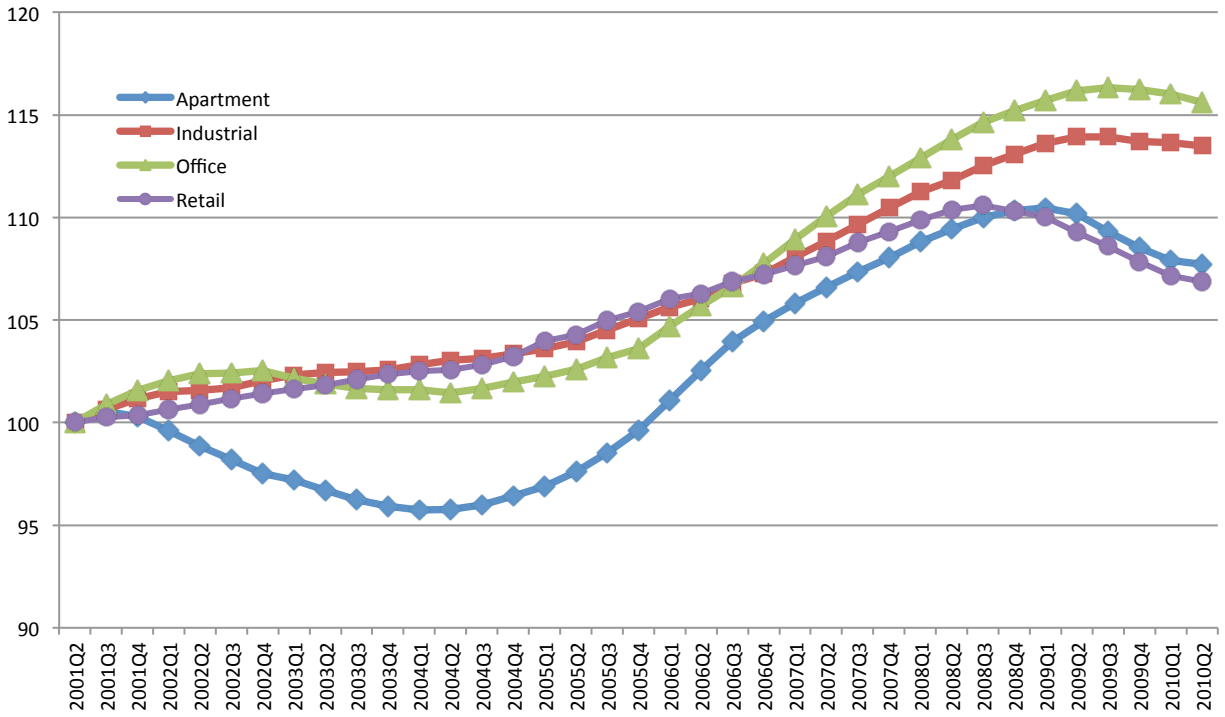


Figure 5 Rental Index by Property Type (GMM Estimates)

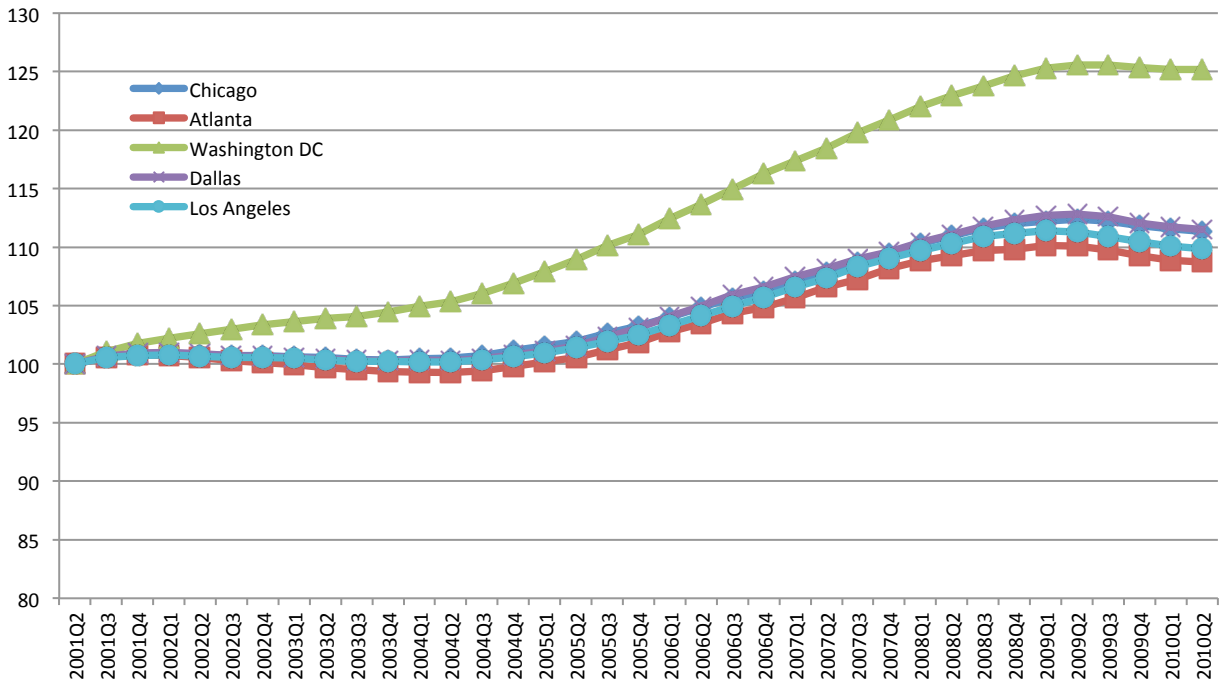


Figure 6 Rental Indices of the Top 5 MSAs (GLS Estimates)

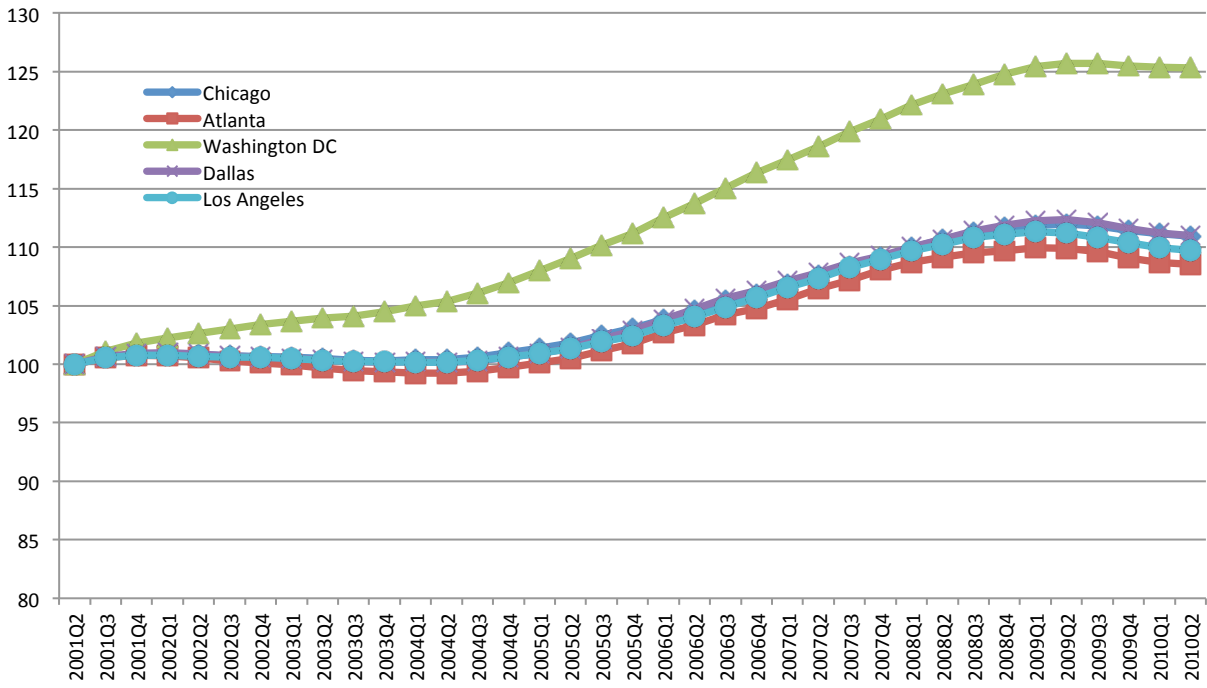


Figure 7 Rental Indices of the Top 5 MSAs (GMM Estimates)

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*** (0.018)	0.675*** (0.019)
ρ	0.512*** (0.000)	0.384*** (0.000)
σ_{ε} *100	2.755	3.696
β *100	-0.170*** (0.040)	-0.199*** (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: $r_{it} = \alpha_i + I_t + \beta \cdot \text{age}_{it} + u_{it}$; $I_t = a + \rho I_{t-1} + \varepsilon_t$, 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 7.

Table 4: Comparison of the Dynamic Panel Data Model Estimates and AR Model Estimates of the Time Series Dynamics of Market-Wide Rental Growth

	GLS Estimates	GMM Estimates	AR Estimates
Mean-reversion parameter	0.51	0.38	0.92
Long term average rent growth (%)	1.03	1.10	8.75
Rental growth volatility (%)	2.76	3.70	0.57

Note: The model is: $I_t = a + \rho I_{t-1} + \varepsilon_t$, where I_t is the market-wide rent growth, and ε_t is disturbance. The GLS and GMM estimates are from the Panel Data Model based on individual property data. The AR estimates are from an AR(1) model based on rental growth time series.

Table 5: Dynamic Panel Data Model Estimates, by Property Type

	Apartment		Industrial		Office		Retail	
	GLS	GMM	GLS	GMM	GLS	GMM	GLS	GMM
a *100	0.113*** (0.023)	0.184*** (0.026)	0.754*** (0.030)	0.925*** (0.031)	0.603*** (0.041)	0.893*** (0.046)	0.462*** (0.051)	0.545*** (0.054)
ρ	0.745*** (0.004)	0.662*** (0.004)	0.438*** (0.003)	0.328*** (0.003)	0.546*** (0.003)	0.406*** (0.004)	0.369*** (0.005)	0.246*** (0.005)
σ _ε *100	1.518	2.168	3.113	3.877	2.475	3.428	4.326	5.210
β *100	0.171* (0.079)	0.215** (0.075)	-0.362*** (0.061)	-0.383*** (0.055)	-0.513*** (0.094)	-0.619*** (0.082)	0.231** (0.089)	0.260*** (0.079)
Long term rent growth $(\frac{\alpha}{1-\rho}) *100$	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: $r_{it} = \alpha_i + I_t + \beta \cdot \text{age}_{it} + u_{it}$; $I_t = a + \rho I_{t-1} + \varepsilon_t$, 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 7.

Table 6: 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*** (0.092)	0.782*** (0.086)	0.755*** (0.073)	0.604*** (0.067)	2.297*** (0.095)	1.889*** (0.087)	0.927*** (0.084)	0.717*** (0.078)	0.818*** (0.098)	0.659** (0.090)
ρ	0.184*** 0.007	0.294*** 0.007	0.171*** 0.007	0.307*** 0.007	0.186*** 0.008	0.318*** 0.008	0.217*** 0.008	0.350*** 0.008	0.197*** 0.008	0.330** 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
β *100	-0.562*** 0.124	-0.506*** 0.133	-0.882*** 0.106	-0.853*** 0.116	-0.501*** 0.131	-0.468*** 0.142	-1.041*** 0.124	-0.967*** 0.136	-0.102 0.138	-0.089 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: $r_{it} = \alpha_i + I_t + \beta \cdot \text{age}_{it} + u_{it}$; $I_t = a + \rho I_{t-1} + \varepsilon_t$, 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 7.

Table 7 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 8 Regression of Rent Growth on Cap Rate

Dependent variable: Rent Growth Estimate

Panel A	(1)	(2)	(3)	(4)
1-quarter lag of transaction cap rate	-0.01*** (0.001)			
2-quarter lag of transaction cap rate		-0.01*** (0.001)		
3-quarter lag of transaction cap rate			-0.01*** (0.002)	
4-quarter lag of transaction cap rate				-0.01*** (0.002)
Observations	36	36	36	36
R-square	0.63	0.61	0.50	0.36
Adj. R-square	0.61	0.60	0.49	0.34
Panel B	(1)	(2)	(3)	(4)
1-quarter lag of current value cap rate	-0.54*** (0.083)			
2-quarter lag of current value cap rate		-0.49*** (0.084)		
3-quarter lag of current value cap rate			-0.42*** (0.086)	
4-quarter lag of current value cap rate				-0.34*** (0.087)
Apartment	-0.48** (0.222)	-0.42* (0.226)	-0.33 (0.231)	-0.25 (0.236)
Industrial	0.46** (0.207)	0.44** (0.212)	0.42* (0.218)	0.41* (0.224)
Office	0.36* (0.206)	0.37* (0.211)	0.37* (0.218)	0.38* (0.224)
Intercept	-0.09 (0.147)	-0.10 (0.150)	-0.11 (0.155)	-0.13 (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 $p < 0.10$. Panel A are results from regression: $r_{t+1} = a + \gamma c_t + \varepsilon_{t+1}$, where c_t is the cap rate in quarter t , and r_{t+1} is the l -quarter lead of rent growth. Panel B are results from panel regressions with fixed effects: $r_{i,t+1} = a_i + \gamma c_{i,t} + \varepsilon_{i,t+1}$, $l = 1, 2, 3, 4$, where $c_{i,t}$ is the cap rate for property type i in quarter t , and $r_{i,t+1}$ 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 9 Regression of NOI Growth on Cap Rate

Dependent variable: NOI Growth

Panel A	(1)	(2)	(3)	(4)
1-quarter lag of transaction cap rate	-0.01*** (0.002)			
2-quarter lag of transaction cap rate		-0.01*** (0.002)		
3-quarter lag of transaction cap rate			-0.01*** (0.002)	
4-quarter lag of transaction cap rate				-0.01*** (0.002)
Observations	36	36	36	36
R-square	0.25	0.25	0.15	0.22
Adj. R-square	0.22	0.23	0.12	0.20
Panel B	(1)	(2)	(3)	(4)
1-quarter lag of current value cap rate	-0.37*** (0.090)			
2-quarter lag of current value cap rate		-0.28*** (0.091)		
3-quarter lag of current value cap rate			-0.21** (0.092)	
4-quarter lag of current value cap rate				-0.17* (0.092)
Apartment	-0.31 (0.241)	-0.21 (0.246)	-0.14 (0.248)	-0.10 (0.248)
Industrial	-0.17 (0.225)	-0.20 (0.231)	-0.21 (0.234)	-0.22 (0.235)
Office	-0.14 (0.224)	-0.13 (0.230)	-0.13 (0.233)	-0.12 (0.234)
Intercept	0.15 (0.160)	0.13 (0.163)	0.12 (0.166)	0.11 (0.167)
Observations	144	144	144	144
R-square	0.12	0.08	0.05	0.04
Adj. R-square	0.11	0.07	0.04	0.04

Note: Standard errors in parentheses. *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.10$. Panel A are results from regression: $r_{t+1} = a + \gamma c_t + \varepsilon_{t+1}$, where c_t is the cap rate in quarter t , and r_{t+1} is the l -quarter lead of NOI growth. These are the results from panel regressions with fixed effects: $r_{i,t+1} = a_i + \gamma c_{i,t} + \varepsilon_{i,t+1}$, $l = 1, 2, 3, 4$, where $c_{i,t}$ is the cap rate for property type i in quarter t , and $r_{i,t+1}$ is the l -quarter lead of NOI 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 value-weighted average NOI growth from NCREIF. The cap rate is the value-weighted average cap rate from NCREIF. All variables are standardized before running the regression.

Table 10 Commercial Real Estate Price Return Panel Data Regression

Dependent variable: NCREIF price return

	(1)	(2)	(3)
Rent growth estimate	0.36*** (0.080)	0.13* (0.069)	0.22** (0.069)
10-year Treasury rate		0.41*** (0.092)	
NCREIF commercial mortgage interest rate			0.154 (0.088)
CMBS issuance relative to commercial real estate sales		0.26** (0.087)	0.42*** (0.090)
Apartment	-0.17 (0.222)	-0.16 (0.175)	-0.16 (0.185)
Industrial	-0.39* (0.223)	-0.31* (0.177)	-0.34 (0.187)
Office	-0.42* (0.224)	-0.32* (0.177)	-0.36 (0.187)
Intercept	0.24 (0.158)	0.20 (0.125)	0.22 (0.132)
Observations	144	144	144
R-square	0.14	0.47	0.41
Adj. R-square	0.12	0.45	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: $p_{i,t} = \alpha_i + \gamma r_{i,t} + X_{i,t}\eta + \varepsilon_{i,t}$, 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.