Analyzing Time Series and Cross Section Rent Data: An Illustration Using US Retail Data

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Abstract

Real estate research has a long and extensive history of analyzing rent dynamics. Due to data constraints, the retail market has been the least researched segment and, more generally, regional panels of data have been rarely analyzed. In this paper, we analyze rent dynamics at the Metropolitan Statistical Area (MSA) level by applying an error correction model, covering almost three decades of retail rent data for the 13 largest MSAs of the United States. We feature the joint analysis of time series and cross section space market data.

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1. Introduction

Real estate research has a long and extensive history of analyzing rent dynamics. The recent literature on the modelling of space markets has settled on an Error Correction Model (ECM) approach in which rents and vacancy rates change according to both changes in the explanatory variables (the 'shock' variables) and to lagged adjustments to the equilibrium long term relationship among the variables [Englund, Gunnelin, Hendershott and Soderberg (2008, hereafter EGHS), and Hendershott, Lizieri and MacGregor (2009, hereafter HLM)].[1]

Research on panel estimation in real estate markets is more limited. Hendershott, MacGregor and White (2002) and Hendershott and MacGregor (2005) applied the Hendershott, MacGregor and Tse (2002, hereafter HMT) model to panels of regional office and retail rents in the UK and to office and retail cap rates in US MSAs, respectively. Mouzakis and Richards (2007) estimated a panel office rents in 12 European cities and Brounen and Jennen (2009ab) have recently estimated panels for European and US city office market rents. Both sets of authors used the basic HMT approach.

However little research has examined the cross section dimension in the pooled data to consider variation in rent determination. Only Hendershott, MacGregor and White (2002) have looked at the cross sectional variations and constructed partitions of similar markets, although a number of studies have sought to explain cross sectional variation in a pooled data set - Shilling *et al*. (1987) consider vacancy rates and Eppli *et al*. (1998) consider returns.

Data limitations, rather than the unimportance of retail real estate, account for the limited research on this sector. To illustrate, the US Census Bureau estimated that consumers spent nearly $4 trillion in the numerous retail outlets across the US in 2008. Moreover, at the end of

[1] Early research on the retail market includes Key *et al*. (1994) who modeled regional and national UK as a function of demand and supply conditions and Tsolacos (1995) who linked retail market rental values to broad economic forces and trends in the retail property markets.

2008 over 27 percent of the North American REIT market capital was allocated to retail assets (Ernst and Young, 2009).

In this paper, we use a pool of retail data to consider the dynamics of the retail space market. We utilize annual MSA retail rent, supply and "vacancy" data provided by Torto Wheaton Research for the 13 largest US retail markets over the 1982-2007 period. We believe we make original contributions to the general analysis of time-series, cross sectional estimation. This includes consideration of how underlying model parameters might be expected to vary in cross section and how markets might best be partitioned into groups with similar dynamics.[2]

The paper is arranged as follows. In the next two sections, we discuss the framework to be estimated and describe the data employed. In the following two sections we report results and summarize our main conclusions and implications for further work.

2. Modelling

The model must address analysis of both time series and cross section data. We begin with the former.

Time series modeling

The time series analysis is similar to the three equation model (rent, vacancy rate and change in supply) that EGHS (2008) estimate for the Stockholm office market and HLM (2009) use to test for asymmetric responses to demand and supply shocks in the London office market. See EGHS and HMT, who introduce the Error Correction approach to rent modeling, for reviews of the earlier time series literature on rent determination.

We begin by specifying the long run demand for space, *D*, as a logarithmic function of real effective rent on new contracts (*R*) and real retail sales (*RS*):

$$D = \lambda_0 R^{\lambda_1} RS^{\lambda_2} \tag{1}$$

[2] There is a literature on the most appropriate spatial categories for portfolio construction – see, for example, for the UK, Hamelink, Hoesli, Lizieri and MacGregor (2000) and Hoesli, Lizieri and MacGregor (1997); for the US, Hartzell, Heckman and Miles (1986) and Mueller (1993).

where λ_1 is the 'price' elasticity (negative) and λ_2 is the income elasticity (positive).

The market clearing (equilibrium) rent equates demand and supply (SU) when the vacancy rate is at its constant 'natural' level (v*):

$$D(R, RS) = (1 - v^*)SU \tag{2}$$

Substituting equation (1) into (2) and solving for R, we obtain:

$$R = \gamma_0 RS^{\gamma_1}[(1 - v^*)SU]^{\gamma_2} \tag{2'}$$

and taking logs gives:

$$\ln R = \ln \gamma_0 + \gamma_1 \ln RS + \gamma_2 \ln(1 - v^*) + \gamma_2 \ln SU \tag{3}$$

In estimation, the underlying elasticities can be obtained from the coefficients as $\lambda_1 = 1/\gamma_2$ and $\lambda_2 = -\gamma_1/\gamma_2$. The estimated constant term is $\ln \gamma_0 + \gamma_2 \ln(1 - v^*)$. Because gamma zero is unknown, the natural vacancy rate cannot be solved from this estimation.

It is common, although not universal (see EGHS) to consider an equilibrium in which average real rental growth is zero (and the vacancy rate is constant). If we further assume the ratio of retail sales to space is constant, γ_1 and γ_2 are equal in magnitude but opposite in sign. A corollary is that the income elasticity ($-\gamma_1/\gamma_2$) is 1.

The short-run rent adjustment equation (introducing time subscripts) is:

$$\Delta \ln R_t = \alpha_1 \Delta \ln RS_t + \alpha_2 \Delta \ln SU_t + \alpha_3 (v_{t-1} - v^*) + \alpha_4 \varepsilon_{t-1} \tag{4}$$

Rents adjust to changes in the shock variables (*RS* and *SU*) and to lagged disequilibrium in vacancy and rent, the latter being the lagged error in the long-run rent equation. Because v* is unobservable, equation (4) is estimated as:

$$\Delta \ln R_t = \alpha_0 + \alpha_1 \Delta \ln RS_t + \alpha_2 \Delta \ln SU_t + \alpha_3 v_{t-1} + \alpha_4 \varepsilon_{t-1} \tag{4'}$$

with $-\alpha_0/\alpha_3$ providing an estimate of the natural vacancy rate.

Because the natural (equilibrium) vacancy rate is assumed constant, there is no long-run vacancy equation. And an equation for changes in the vacancy rate can be expressed as a direct analogue to the rental change equation. The final equation in the model is for the change in supply. In this version of the paper, we limit ourselves to estimation of the rent component of the model.

Cross section modeling

We could have variation in v* and in the demand elasticities across MSAs.[3] To allow the natural vacancy rate to vary in cross-section estimation, we must allow the constants in equations (3) and (4') to vary in the estimation.

To allow the income and price elasticities to vary in cross-section we need to allow γ_1 and γ_2, the retail sales and supply coefficients, to vary. The retail sales coefficient amplifies (greater than unity) or dampens (less than unity) the impact of growth in retail sales on rents. The supply coefficient has a similar amplifying or dampening effect on the transmission of the impact of a change in supply to a change in rent. Because we expect γ_1 and γ_2 to be roughly equal and opposite in sign, we expect a negative correlation of the cross section gammas.

3. Data

Our private retail real estate data on rents, supply and 'vacancies' have been kindly provided by Torto Wheaton Research (TWR) for the largest 13 US MSAs. We supplement these data with MSA level CPI deflators and real retail sales data. These series are discussed in turn and a range of summary statistics is provided. We have annual data for 1982-2007.

Real Retail Rent

TWR rent indices are constructed from both information produced through leasing agreements that CB Richard Ellis (CBRE) has been involved with and property level asking rents from CoStar. TWR has estimated a hedonic rent index along the lines of Wheaton and Torto (1994) and EGHS

[3] See the discussion in Hendershott and Haurin (1988) on evidence of variation of office market v* across MSAs.

(2008).[4] The underlying leases are for tenants in neighborhood and community market centers (regional and super regional center tenants are excluded due to lack of sufficient individual leases). TWRs standard lease has a five year term and is the gross rent for 5000 square feet in an existing center. We convert nominal series to real series using the BLS consumer price indices for our MSAs based on the prices paid by urban consumers for a representative basket of goods and services. These indices are based at 1982=100. NY, DC and LA had the highest real rents, all being $13 per square foot in 1982 and about the same in 2007.

Figure 1 is a box plot (from Eviews) showing the mean percentage change in real retail rents as a solid dot surrounded by a box whose lower and upper boundaries are determined by, respectively, the first and third quartile of observations. The horizontal stripes represent the maximum and minimum observation in case of no outliers. When outliers, indicated with circles in the graph, are present, the stripes represent the observations with the largest distance from the mean within the non-outlier range.[5]

[Insert Figure 1 around here]

Nine of thirteen markets show negative average real rental growth over the 1982-2007 period. Boston and Dallas have the largest declines; Phoenix is a large outlier with an average positive growth of 1.4% per annum. (As discussed below, Phoenix had far and away the largest percentage growth in real retail sales over the period, and Boston had the smallest growth.)

All thirteen MSAs had declines in real rents between (roughly) 1984-87 and 1992-94. On average the decrease was 28 percent with eight of the 13 MSAs showing a decline of more than 25 percent. Hendershott and Kane (1992) attribute the general decline in real estate rents and values during the late 1980s and early 1990s to massive overbuilding during the middle 1980s (the 1990-91 recession also contributed). The overbuilding resulted largely from two provisions in 1981 tax legislation. First, extremely generous tax depreciation allowances were adopted (complete write-off of structures investment in 15 years). Second, 'passive losses' were made deductible against wage income. (1986 legislation more than reversed these provisions.) In

[4] Information on retail rent indices is based on a TWR publication (Marks, 2008).

[5] Outliers are those observations whose value does not fall within an interval determined as first quartile minus 1.5 times IQR or third quartile plus 1.5 times IQR, IQR being the Inter Quartile Range or the difference between the third and first quartile observations.

addition, financial institutions were encouraged to invest in commercial mortgages, providing cheap funding for these investments.

Real rents then rebounded somewhat in most markets, with Houston and Phoenix more than reversing their earlier declines. The exceptions were Boston and Dallas, which experienced even further declines, ending the sample period at $7 psf; only one other MSA had rent (barely) below $10 in 2007. NY had the greatest volatility, owing to enormous rent increases in the early 1980s (rent rose from $13 to $24), before exactly reversing.

Availability Rate

US office and industrial property rent research has emphasized responses to gaps between the actual and natural vacancy rates. TWR argue that the vacancy rate is less relevant to shopping centers and that availability rates are a better measure of market tightness. These rates reflect both vacant space and occupied space that could be available to let (space that is currently occupied by tenants whose leases are rolling over and space with leases that the landlord can cancel). We use the TWR availability rates, the percentage of retail stock that is available to rent, in our analysis.

Figure 2 reports a box plot for the 13 MSAs. There is a huge range of average values, from a low of 4 percent in NY and Washington DC to 16 percent in Riverside. The latter was in the 15 to 22 percent range until 2004, before plunging to 6 percent in 2006.

[Insert Figure 2 around here]

Stock

TWR has compiled these series based on information provided by the National Research Bureau Shopping Center Directory (a subsidiary of CoStar) and TRW/Dodge Pipeline. We believe the data exclude space in regional and super regional centers. Periodical increases in the supply of retail space represent both the opening of new centers and the additional available space as a result of expansion of existing centers. The data we use are in thousands of square feet. Minneapolis, NY, Riverside and Seattle have less space (starting around 10,000 and rising to 20,000). Chicago has the most space, rising from 40,000 to 94,000.

The mean percentage change in retail supply in the 13 MSAs varies within a rather tight band of 2.2 to 4.5 percent but with some remarkable positive outliers due to the bulky nature of shopping centers as shown in the box plot (Figure 3). All MSAs except those on the east coast exhibited particularly rapid growth in the 1984-90 period, consistent with the argument of Hendershott and Kane (1992).

[Insert Figure 3 around here]

Real Retail Sales

The US Bureau of Census (BOC) publishes retail sales data at the MSA level based on surveys of companies with one or more establishments that sell merchandise and related services to final consumers. The monthly series date back to 1951. New samples are surveyed every five years.[6] The data are in billions of dollars. Three MSAs – NY, LA and Chicago -- have had sales roughly 50 percent greater than the other ten.

A box plot contains data on percentage changes in real retail sales per square foot. Only one MSA has an average change greater than 0.2 percent (Phoenix with 1.3%), and six MSAs have declines of a half percent or more. The largest average declines are 1.5% in Chicago and 1.2% in Los Angeles.

[Insert Figure 4 around here]

4. Estimation

The first panel of Table 1 gives our estimates where only the constant, $\ln \gamma_0 + \gamma_2 \ln(1\text{-}v^*)$, varies in cross-section.[7] In this estimation the RS and SU coefficients are $\gamma_1 = 0.55$ and $\gamma_2 = -0.65$, giving an income elasticity of 0.84. This suggests that an equilibrium of zero rental growth and vacancy at the natural rate is produced when supply rises at a rate of 84% that of real sales and, thus, there are space efficiency gains.[8] The implied price elasticity is -1.54.

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[6] Estimates by the BOC show that online sales currently represent about three percent of total retail sales.
[7] The normal econometric requirements of co-integration and order of integration are met.

[8] In sample, we have supply increasing more than real sales (3.1% versus 2.7%) and thus a fall in space efficiency. We also have rents falling (by 0.3%) and the vacancy rate rising (by 1.15 percentage points). These figures may be due to the stages of the cycle at the start and end of the period.

[Insert Table 1 around here]

Next, we allow all coefficients to vary in cross-section, in effect, estimating separate models for each city. We do not report these results, but summarize some of them. We expect that γ_1 and γ_2 would be highly negatively correlated, and they are: the sample figure is -0.75. Estimates of γ_2 are generally in the range of -0.3 to -1.0. Given that the average vacancy rate (a proxy for v*) is typically less than 15 per cent, we would expect the constant to be negatively correlated with γ_2, depending on the variations in γ_0. The correlation from our data is negative, but only -0.34, suggesting the importance of variation in ln γ_0.

While the above suggests a relationship between γ_1 and γ_2, it gives no indication of what the magnitude of these coefficients might be, or what might cause cross-sectional variation. We correlate the cross section coefficients, γ_1 and γ_2, with the key variables and look for significant relationships.

The supply coefficient correlates significantly and positively with the mean (0.48) and the standard deviation of supply growth (0.58).[9] As the supply coefficients are negative, this means that the supply coefficient *decreases in magnitude* as these variables increase in value. Thus, the greater is the average supply growth and its volatility in a city, the lower is the magnitude of the supply coefficient and so is the responsiveness of rent.

Constructing panel partitions

We construct partitions based on the retail sales and the supply coefficients as follows:

- For each coefficient, we order the cities according to magnitude of the coefficient;
- Starting from the smallest in magnitude, we test whether there is a significant difference between it and the next city;
- If there is not, we include the second city in the same partition as the first and compare the second and third cities to see whether the third city should be in the partition;
- If there is, we start a new partition and compare the second and third cities;

[9] Because the gammas correlate so strongly with each other, the retail sales correlations are similar.

- We repeat until all cities have been allocated to partitions.

The results and the coefficients are shown in Table 2.

[Insert Table 2 around here]

For the retail sales coefficient, ten of the cities are in the same partition; Houston and New York form a partition with high values of the coefficient; and Boston is alone with its incorrectly signed coefficient. For the supply coefficient, all cities are in two partitions.

Only Boston, Chicago, Dallas and Washington have demand and supply coefficients that are significantly different in magnitude at the 5 percent level. For Dallas and Washington, the supply coefficient is significantly greater in magnitude than the retail sales coefficient; the opposite is true for Chicago; and, for Boston, the retail sales coefficient is smaller in magnitude than the supply coefficient but it is negative.

These considerations suggest three clear partitions and one 'orphan', Boston with the negative retail sales coefficient. We discard Boston from further analysis and continue with the partitions. Because Houston and New York are separate for retail sales, we place then in a separate partition. As the other cities split in two for supply, we keep this distinction. Table 3 lists the final partitions.

[Insert Table 3 around here]

The second through fourth columns of Table 1 report estimates of the long run rent model for the three partitions. The three partitions have retail sales and supply coefficients that differ significantly among the partitions.

Short run rent models

Table 4 shows the preferred short run rent models for all cities except Boston together and for the three partitions. In estimating these models, we tested the first and second lags of the retail sales and supply and the second and third lags of the rent error and the vacancy rate. All variables except supply are correctly signed and highly significant in the common model and two lags of rent are significant. The adjusted R^2 is 77%.

[Insert Table 4 around here]

For partition 1, two lags of rent are significant; retail sales are not significant but supply is, and the rent and vacancy errors are significant. The adjusted R^2 is 44%. For partition 2, all coefficients except that on supply are significant and we use a two period lag of the vacancy rate. The adjusted R^2 is 71%. Lastly, for partition 3 lagged rents, retail sales (at 8%) and the rent error are significant. Neither supply nor the lagged vacancy rate is significant. With neither the constant nor the vacancy rate coefficient significant, the estimates of the natural vacancy rates are poor and highly sensitive to the form of the short run equation (the number and composition of lagged relationships included).

To summarize, the rent error is always significant and in the range 0.17-0.20 except for partition 3, where it is 0.39. The vacancy rate error is significant except for partition 3 and is in the range 0.40-0.60. That is, for partition 3, the rent error does "double" duty.

At the far right, Table 5 lists the mean vacancy rates and the natural rates that come from the common and the partitioned equations. The implied natural vacancy estimates from the common model correlate at 96 percent with the period averages, although on average they are one percentage lower. For the partition estimates the correlation is close to zero (0.017) but rises to 0.68 when Houston and New York are excluded, and the averages are only 0.2 percentage points different. As noted above, the partition 3 estimates are based on two insignificant coefficients (the constant and the vacancy rate) are highly variable depending on the chosen form of the short run equation.

Comparing the LR and SR models

The short and long run coefficients are compared in Table 5. The short run retail sales coefficients are in the range of 32-41 percent of the value of the equivalent long run coefficients. Only one short run supply coefficient is significant and it is around half the magnitude of the equivalent long run coefficient.

[Insert Table 5 around here]

5. Conclusion and Further Research

The above analysis has substantially extended work on pooled data for the investigation of the dynamics of real estate space markets. It has confirmed the value of the ECM approach. The basic findings show that rent responds partially, but within period, to changes in the activity measure, in this case, retail sales. In contrast, responses to supply are not contemporaneous but take place through the lagged rent and vacancy rate errors. The essential structure of these models is robust against the lag structures employed for the lagged dependent variable and the shock variables with one exception.

The vacancy rate error in one of our partitions is highly insignificant and sensitive to the lag structure. Together with a similarly volatile and insignificant constant, this produces unreasonable estimates of the natural vacancy rate. We suspect this is due to only having two MSAs with extreme LR coefficients in that partition. We have estimated short-run basic vacancy rate models that have significant supply and vacancy error terms and that produce stable and accurate estimates of the natural vacancy rate. We will report and analyse these in the next version of the paper.

Our analysis of the parameters of the long run model confirms the implied structure and relationships among the coefficients. The partitioning of the long run model reveals the varying spatial dynamics across MSAs and the different price elasticities. Changes to retail sales and supply are transmitted differently to rents in different MSAs. Our preliminary work suggests that the variances of the explanatory variables provides some explanation of these cross-section variations and thus suggests that a basic options analysis applies.

In the next stage of this project, we will:

- Report the vacancy rate estimation and obtain estimates of the implied natural vacancy rate jointly with estimates of the rent equations;
- Seek to develop an equation for supply;
- Develop an options-based analysis of the cross-section variation in the key long run parameters; and
- Give consideration to asymmetries.

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