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Matt Larriva, CFA · Peter Linneman, PhD.

Abstract Purpose

To explain both national and market-level cap rate changes as simply an interaction between Gross Domestic Product and Consumer Price Index.

Design/Methodology/Approach

We use a binary logistic regression with binary independent variables, trained on a synthetic minority over-sampling set, to explain cap rate expansion and contraction at the national level and at 20 MSAs.

Results

Both the national model and the MSA models capture around 40% of all cap rate expansion periods with a robust confusion matrix.

Originality

This model contributes to the existing corpus by 1) establishing a statistically significant relationship between GDP, CPI, and cap rates which 2) holds explanatory power at the national and MSA levels, by 3) mapping the ground truth from scalar to binary.

Practical Implications

The accuracy of the model suggests a simpler and more robust explanation for understanding cap rates and navigating property markets in an environment of fluctuating interest rates.

Keywords Binary Logistic Regression · Cap Rates · US Real Estate Markets · Multifamily Cap Rate · United States · Apartment Cap Rate

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Address(es) of author(s) should be given

1 Introduction

2 Literature Review

The literature on cap rate forecasting is extensive, and it can be viewed well through two different lenses. One framework which groups the research nicely is illustrated in Ghysels et. al. Forecasting Real Estate Prices (Ghysels et al., 2013) which divides the literature by variable selection. The authors enumerate three camps: those which use lagged return (or price change) as a variable, those which use ratios such as rent-to-price or price-to-income, and those which use more granular property or regional data.

Another valid lens by which to view the research is through methodology selection, as documented by Larriva and Linneman (Larriva and Linneman, 2021). The authors divide the research into simple time series methods, multivariate timeseries, and machine learning methods. The division is roughly chronological.

Neither lens quite suits the study's purpose: the variables used in this work are not often found in the research. More common is a spread to an inflation metric or a derivative of GDP. Separately, the level of granularity we seek to explain is uncommon (MSA level). More common is either property-level or national. Finally, the method we use is new to the research, to our review. The following section, then will seek to outline research that contains either GDP or inflationary metrics, or their derivatives, regardless of method or granularity.

In the mid-1990s, research was concentrated on either single-variate autoregressive methods (Gau, 1984), (Gau, 1985), (Linneman, 1986) or variations on OLS that used multi-stage estimation (Case and Shiller, 1990), (Abraham and Hendershott, 1994). The variables used in these methods of forecasting tended to fall into classes that line up with the components of a cap rate: risk-free rate, real interest rates, relative return expectations, and risk. Many models' variables included a government long bond to capture the risk-free and real rates, an economic spread (credit or pricing-based) to capture the relative expense or return of real estate, and macroeconomic factors to capture the growth prospects and risk in the marketplace. Some models included a term to capture forward estimates including either sentiment or expected rent or NOI growth. This lines up with the Gordon growth model of pricing cap rates as the discount rate less the perpetual NOI growth rate. Thus, the value of macroeconomic factors, or their derivatives, was established.

2.1 Inflation

Around 2000, more attention was dedicated to inflation as a primary determinant of cap rates.(Costello et al., 2001; Sivitanides et al., 2001; Chandrashekaran and Young, 2000). In general, the research has reached mixed conclusions on the ability of changes in inflation rates to determine future changes in cap rates. Conclusions range from an implied correlation between inflation and cap rates to emphatic empirical support of the inflation rates' predictive ability to dismissal of the relationship between inflation rates and cap rates entirely.

These different conclusions can be attributed to differences in data and methodology. Research which finds that inflation is a good predictor of future cap rates typically use time series data for both macroeconomic variables and cap rates while research which dismisses the value of inflation rates, generally, use cross sectional econometric methods.

In contrast to that, however the Larriva and Linneman work used timeseries analysis and espouse that inflation is a non-integral variable to cap rate forecasting and explanation. Their model used granger causality to select variables and establish a highly robust explanatory and predictive VECM model, without the use of interest rates.

Sivitanides, et. al. (2001): finds that increase in economy-wide inflation lowers cap rate. Argue that 1• Tries to answer question: Do appraisals generate valuation estimates that move with the opportunity cost of capital, and that reflect realistic expectations about future income growth and risk? • Data used: APPRAISAL BASED, spanning 16 years across 14 metropolitan markets o NCREIF database • Type of model: Panel-based, rather than just time series o Addition of cross-section variation to time series gives greater data richness and yields robust statistical results • Why different: o First to systematically examine NCREIF cap rates at the local level • More findings: o NCREIF cap rates move exactly as PE ratios do, but only if appraisers form expectations about future income growth by looking backward, not forward (i.e. past income/rent growth seems to be extrapolated forward) o Suggest it is possible to forecast appraisal-based cap rates

Costello et al. in "Real Estate Risk: A Forward Looking Approach Real Estate Risk: A Forward Looking Approach" provide an example of re-

searchers reaching a conclusion that inflation has a serious effect on cap rates.To do this Costello et al. measure future risk of real estate assets using a variance auto regression (VAR) method and conclude that the risk of the given asset is the standard error of each variable.(Costello et al., 2001) Their approach shows that the cap rate can be predicted using local market rent forecasts as well as national interest rate and inflation forecasts. Costello et al. make two very important conclusions. First, cap rates reflect changes in the opportunity cost of riskless capital relative to inflation. Second, cap rates are related to recent market rent growth instead of forecasted rent growth. (Costello et al., 2001) In other words macroeconomic variables such as inflation have a definite effect on cap rates.

Sivitanides et al.use the average cap rates over the past 16 years of four property types across 14 metropolitan markets to examine how cap rates behave. This data is extracted from the National Council of Real Estate Investment Fiduciaries (NCREIF). Sivitanides et al.'s methodology takes great advantage of their data. A log-linear model yielded the best results due to the non-linear nature of the data. (Sivitanides et al., 2001) This statistical specification was estimated using a dual Time-Series Cross-Section method which corrects for cross section correlations and group-wise heteroskedasticity. Inflation was found to be a major driver of cap rates. In fact, Sivitanides et al. found that an expected increase in economy wide inflation of one percent annually lowers office cap rates by 46 basis points, multi-family cap rates by 40 basis points, retail cap rates by 54 basis points, and by 20 basis points in industrial cap rates.

In contrast to Costello et al. and Sivitanides et al., Chandrashekaran and Young find that there is little to no relationship between inflation and cap rates. To reach this conclusion Chandrashekaran and Young use two regression models: one with macroeconomic variables and one with lagged cap rates. The model with lagged cap rates uniformly performed better. (Chandrashekaran

and Young, 2000) The duo concluded that their attempt to predict cap rates using macroeconomic variables, such as inflation, were unsuccessful. Gimpele- vich supports Chandrashekaran and Young using Monte Carlo simulations of real estate returns called the Simulation-Based Excess Return Model (SERM). The simulation results in poor correlation between inflation rates and cap rates (Gimpelevich, 2011).

2.2 GDP

“Global Real Estate Markets – Cycles and Fundamentals” Case, et. al. (2000): find that international property returns move together in dramatic fashion. Attribute substantial amount of correlation across world property markets to effects of changes in GNP • RE business distinguished by fact that its “product” is not portable – all competition is local. Thus, would naturally expect correlation of changes in property values to diminish as distance between spaces increases. However, paper finds that there is material co-movement in property returns at the international level • Find that correlations of real estate are due in part to common exposure to fluctuations in the global economy, as measured by an equal-weighted index of international GDP changes • Data used: multiple sources stitched together, time span 1987 – 1997 (p.5) o International Commercial Property Associates dataset (dissolved and formed into ONCOR International) o Hillier Parker European survey • Type of model: remove effect of country’s own GDP on its property return series through univariate linear regressions of the return series on contemporaneous GDP changes o Then, for each property type, compare correlation matrices of raw returns and of the regression residuals

“Follow the Leader: How Changes in Residential and Non-residential Investment Predict Changes in GDP” Green (1997): employs Granger causation model to test whether residential and non-residential investment Granger cause GDP, or vice versa. Finds that, under a wide variety of time series specifications, residential investment causes GDP, while non-residential investment is caused by GDP (note: the paper uses phrasing “causes GDP” which is a little non-intuitive, but as I understand it, it means to cause creation of Gross Domestic Product) • Perhaps residential investment is merely a predictor of GDP, rather than causer • Can extrapolate from this “flow of funds” analysis to potentially apply to what happens when or is implied by reduced GDP / lower GDP growth • Note: this paper seems written to combat proposed changes to the tax code that would have hampered residential investment benefits • Data used: from Citibase spanning 1959-1992, all series in 1987 dollars o Real GDP o Real private domestic non-residential investment o Real domestic residential investment • Model type: Granger tests / Granger causality

GDP, unlike inflation, is a fairly obvious driver of property values and consequently cap rates (Quan and Titman, 2003). As the GDP or wealth of a nation, or even a region, rises the value of property in that nation or region would presumably rise. The primary question in the literature concerning GDP and cap rates is how GDP effects property values and cap rates. If GDP is a primary driver of property values and cap rates, does where GDP growth occur matter in real estate pricing? If GDP is growing locally will that have a stronger effect on local real estate values than global GDP growth?

Since, GDP, presumably, does have a significant effect on property val- ues and cap rates, does worldwide GDP growth or local GDP growth have a larger effect on property values and cap rates? Goetzmann and Rouwenshorst explore whether or not correlations across global real estate markets are due to world changes in GDP, and estimate the value of local economic performance in real estate markets. This is an important question in real estate because all real estate is essentially local and if local growth has a stronger effect on property values than national or global growth investors can better leverage local growth patterns to maximize return. It is difficult to obtain international property return data, but Goetzmann and Rouwenshorst collected data from a now de- funct real estate association the International Commercial Property Associates (ICPA). This organization published yield and rent estimates in ICPA’s ”In- ternational Property Bulletin”. Unfortunately, this source among other dated real estate reporting firms do not provide the most useful data.

For example Goetzmann and Rouwenshorst estimate income and capital appreciation with yields and cap rates.

International real estate markets are found to be correlated through changes in world GDP. Some markets, such as Asia, are more effected by lo- cal changes rather than world changes in GDP (Goetzmann and Rouwenhorst, 2000). In other words, even though real estate is fundamentally local changes in the global economy carry enough weight to have significant effects in local real estate markets.

Quan and Titman utilize time series regressions to examine the effects of changes in macroeconomic variables on real estate values and rents. To begin Quan and Titman explore the connection between stock and real estate mar- ket returns, and after establishing their connection the duo explore factors and develop regressions to explain this connection. The first theory they explore is that real estate and stock prices are both guided by future macroeconomic expectations such as GDP growth. The second is that commercial real estate prices rise and fall because of changing political and economic fundamentals, under this theory the relationship between the stock and real estate market will be much weaker. After controlling for macroeconomic variance Quan and Tit- man find that the correlation between real estate and stock prices are primarily because of economic fundamentals, and that rental rates are strongly correlated with GDP growth.

To reach these conclusions the duo used an international data set in- cluding 17 countries with data spread over 14 years. All of the real estate data was obtained from JLL (previously JLW). This data includes estimates of capital and rental values arising from public opinion. In general, international macroe- conomic variables (GDP, exchange rates, inflation, etc...) were all provided by the IMF International Financial Statistics Yearbook. Quan and Titman's first table lays out the mean commercial real estate capital values, commercial rents and the stock index, and the first order serial correlation of the capital appre- ciation series (Quan and Titman, 2003). This chart shows that Asian markets, Hong Kong and Taiwan, experienced large increases in real estate price between 1984 and 1996 while the rest of the world experienced only moderate growth.

In empirical testing the duo utilize both cross sectional and time series econometric meth- ods. Indonesia, Taiwan, and Thailand were excluded from cross-sectional regressions because of a lack of data in the early to mid 1980s. For the remaining countries Quan and Titman calculated the change in the value of stock indices, real estate indices, and macroeconomic variables. Their regression examines the factors of long term appreciation and changes in rental rates of commercial real estate. This cross sectional analysis shows that changes in GDP are very strongly related to movements in real estate values. Despite the significance of GDP inflation and interest rates had relatively little effect on real estate values.

Time series regressions yielded the same results as cross sectional anal- ysis. Real estate values and rents were still significantly affected by changes in GDP. Inflation, again, appears to be unimportant. Concerning inflation, the duo finds that real year-to-year rental rate is negatively effected by inflation (Quan and Titman, 2003). Therefore, real estate may not be a good short term hedge against inflation.

There is a clear desire in academic and professional circles to find a good predictor of cap rates to be able maximize potential returns. Despite the plethora of research attempting to establish the determinants of cap rates there exists a persistent degree of uncertainty in predicting cap rates. In fact, Liang Peng in "Finding Cap Rates: A Property Level Analysis of Commercial Real Estate Pricing" found a strong positive relationship between pricing and risk for all property types. In other words the higher the cap rate the more uncertainty (Peng, 2013). Keeping in mind Peng's findings macroeconomic variables may also contribute to uncertainty in the value of real estate assets. Fundamental macroeconomic variables such as inflation, deflation, and GDP growth despite their potential influence on uncertainty still appear to be the most promising variables for predicting future cap rates.

2.3 GDP and Inflation together

Contemporaneously, research emerged focusing on MSAs in specific as opposed to aggregated cap rates metrics. Campbell et al. (Campbell et al., 2009) forecasted the change in the return premium to housing using a VAR method, including national rent-growth and premiums, local and national income growth, employment growth and population growth. Their model produced in-sample results over the quarters from 1975-2007 of 0.47 at the 25th percentile, and 0.59 at the 75th percentile [their Table 4]. The estimates were for individual MSA's hence the quantile distribution.

Aizenman and Jinjarak (2013): determine that the most economically significant variable in accounting for changes in real estate valuation is lagged real estate valuation appreciation (defined as real estate inflation minus CPI inflation), followed in importance by lagged declines of Current Account / GDP (i.e. Current Account divided by GDP)

"The Other (Commercial) Real Estate Boom and Bust: The Effects of Risk Premia and Regulatory Capture Arbitrage Duca and Ling (2015) [DL]: find that cap rates are positively correlated with inflation (via risk premia), and negatively correlated with rent growth expectations (via GDP) • Split into short run stationary testing and Long-run testing • Expected rent growth has a negative significant relationship with cap rates (p.19); risk premia and real Treasury rates drive cap rates, not the converse o Conforms with broader finance view that asset valuations are most reflective of shifts in discount factor (i.e. required rate of return) rather than change in cash flows • Data used: Real Estate Investment Survey cap rates, published quarterly by Real Estate Research Corporation (RERC) o RERC focuses on institutional grade assets owned by pension/endowment funds life co's etc o Four major property types o 1996-2014 • Type of model: unclear to me – decomposition of estimated long run equilibrium factors

2.4 Similar Models and Novelty

Finally, non-VECM and non-VAR methods have also made recent contributions in the field of cap rate forecasting, especially internationally. In countries where volatility is less consistent or where historical data is more difficult to access, these alternate methods offer unique insight into property value forecasts. The advantage to using non-VAR or non-VECM methods is the ease of model specification and the comparatively little data needed. Of course, the challenge with processing time series data in a linear model usually manifests as autocorrelated residuals stemming from autocorrelated input series.

Emerging markets valuations were well forecasted using multivariate regressions despite the lack of transparent pricing data and the need to incorporate sometimes large risk premiums (Dasgupta and Knapp, 2008). The authors do not discuss this, and present instead their models' R-squared and their coefficients' t-statistics. Further concern arises from the small sample size–25 observations– and very low Degrees of Freedom resulting from upwards of 7 terms' specifications.

Chervachidze and Wheaton (Chervachidze and Wheaton, 2013) address both the (autocorrelation) errors and degrees of freedom by using an MSA-specific panel regression with a fund-flow variable. This was used to generate in-sample R-squared values of 0.86 for Multifamily and 0.629 for Office. Their analysis focuses on periods from Q4 2000 to Q4 2009 and captures much of the cap rate compression and sharp increase during the GFC. The research also nods to the oft-heard criticism regarding NCREIF cap rates, specifically that they are not based on actual sales transactions.

3 Data

For the national model there are three data series that are used: the Consumer Price Index, the Gross Domestic Product, and the nominal Apartment cap rate series.

The Gross Domestic Product is a quarterly, unadjusted (not de-seasoned) series from the St. Louis Fed's economic data page (FRED). It is important to use a nominal (versus real) series, as we are comparing this to the consumer price index, which is a close proxy to the interest rate series used to convert the GDP from nominal to real. That is to say, we would be double counting the impact of inflation.

The Consumer Price Index series is sourced to the Bureau of Labor Statistics, and it is also a non-seasonally adjusted series. In both cases, we did not seek to alter the series with seasonal adjustments because the raw data itself contains information which we do not wish to strip. Knowing if the economy grew faster than inflation, even if it was in 4Q, and even if it was due to holiday sales, is valuable information. Such a situation suggests a very different environment from its seasonally adjusted counterpart which may shows an economy in which 4Q growth is similar to say the prior quarter.

Finally, cap rate series at the national level are sourced to Green Street. Green Street defines its cap rate series as the next-twelve-months' NOI divided by the spot asset value.

MSA-level data follows the conventions of the national data. Non-seasonally adjusted series are selected both for MSA GDP and the MSA's CPI. The former is from FRED while the later is from the Bureau of Labor Statistics.

As national CPI is presented monthly, and national GDP is presented quarterly, we proceded with quarterly data for the national model, pairing the CPI release most close to the GDP release.

More challenging was the MSA-level data wherein GDP is presented only annually and CPI is presented with varying frequencies depending on the region. Atlanta is published on even months. Boston is published on odd months, and New York is published monthly. Some are bimonthly. The Bureau of Labor statistics only offers CPI measures for 22 Core Based Statistical Areas. Two of these are "Urban Alaska" and "Urban Hawaii", but these have no equivalent GDP series, so they were discarded. The remaining 20 CBSAs have GDP series. But the GDP series are not necessarily for the exact same areas i.e, some GDPs are published for an MSA, some are published for a CBSA. Adding to this confusion: the BLS revised its reporting in 2018 and started offering CBSA measurements instead of MSA measurements, thus revising the coverage areas.

We attempt to reconcile this by matching MSA to CBSA where needed (between the BLS and Fed). And we average the measurements of CPI over a year before matching them to the GDP metrics. In this way, we end up with 21 geographies: 20 CBSAs and 1 national geography. Each geography has a cap rate, CPI, and GDP.

4 Model Construction

4.1 Model Selection

While most analyses forecasting cap rates allow the random variable to be generated from a normal distribution, we opted instead to represent the variable as generated from a Bernoulli distribution. While this choice might be unorthodox–modeling a continuous variable like percentage as a binary variable– we argue that it is well suited for two reasons.

First, it is practical. Real estate is not an equity, it is an alternative asset. As such, it is illiquid. This lack of liquidity means an investor cannot enter and exit the market readily. As such, a would-be buyer is somewhat ambivalent between caring if a cap rate will go up by 40 basis points next year and if it will simply go up. In either case, next year's prices will offer a better value. Similarly a would-be seller should be ambivalent between knowing if next year a cap rate will go up by 10 basis points or if it will go up by 100. In either situation, next year is a worse time to sell than this year. Contrast this with an equities trader who can easily place stop-losses or 'level-in' to a position. Such a trader cares very much whether his holdings will increase 10% next year, hence estimating liquid asset pricing is well suited by a continuous variable. But estimating illiquid asset pricing is, we argue, better done with a discrete variable.

Second, it maps to the binary nature of the motivation of the model: will GDP growth (contraction) exceed CPI growth (contraction)? It matters less the exact amount one exceede or does not exceed the other. We argue that the question is simply: can a landlord pass on rising expenses to tenants or not? In the case where GDP is rising faster than inflation, we argue the tenants will be wealthier than the growth in expenses, and thus able to absorb higher rents, creating an asset worth more. Conversely, when inflation outpaces the growth of the economy, we argue the tenant is not in a position to absorb higher costs, leaving the landlord to bear them, creating an asset worth less.

Thus a logistic regression with a single binary input lent itself well to our analysis, with cap rate expansion as the response variable, and GDP change ¿ CPI change as the independent variable.

4.2 Model Specification

We preprocessed the GDP and CPI series differently for the national versus MSA model because the national data was more frequent. In both cases, the preprocessing included differencing the series and then creating a simple trailing average. The goal in smoothing the series was to prevent an overly sensitive signal if, say, one period had inflation that quickly reversed.

CPI and GDP percentage changes at t_0 were compared to trailing average historical percentage changes. A signal was generated when 1) the t_0 GDP change was less than its trailing average changes and 2) the t_0 CPI change was greater than its trailing averages. The signal suggests cap rate expansion in the next period.

The cap rate series were simply differenced and their sign taken to be a boolean variable such that cap rate expansion is TRUE and cap rate non-expansion (and contraction) is FALSE.

To establish the validity of the model for predictive power, we trained five separate models (Year = 2015, 2016....2020) which were given historical data and then asked to predict the next years' (Years 2016-2021, 2017-2021,...2021) cap rate expansions and contractions based on the signal series outlined above. This was done once for the national model and once for the MSA model. All MSA models are trained and specified the same. The model was not given the MSA name as a dummy variable.

The ground truth of cap rate expansion does not present a balanced set, as cap rate compressions are far more frequent than cap rate expansions (roughly two to three times more years see compressions than expansions). We overcame the imbalance through a Synthetic Minority Oversampling Technique as created by (Chawla et al., 2002). This balanced the frequency of cap rate expansions and contractions to prevent a the logistic regression from estimating all compressions (which would produce a low-variance high-bias estimator).

4.3 Model Goodness of Fit

In both the National and the MSA models, the logistic regressions displayed consistent coefficients, inline with our hypothesis. The coefficients had low standard errors relative to the coefficients' magnitude, and the 2.5% to 97.5% bounds did not include zero in any case.

Where a year is listed in the Slit-Year column, the data was segmented into training and test sets. The training periods were all prior to the split year, and the test set was the split year through 2021. When "all-time" is listed under the Split-Year, the model was trained on all data and evaluated on all avalailable data.

The columns, "Coef.", "Std.Err.", "Z", "$P > |z|$", and the 2.5% to 97.5% bounds are all populated with the parameters from the trained models using the training data. The columns to the right, "accuracy" through "specificity" are based on the test data.

National models were created every two years from 2000, as data is both more frequent and longer lived than MSA-level data. MSA models were created every year from 2015. It is worth noting that the coefficient decreased consistently as time advances, suggesting that perhaps the signal is not as robust as it once was. However the standard error decreases correspondingly, producing a Z score which is as high as the earlier periods. Still, though the coefficient is decreasing more recently, all of the train/test models had higher coefficients for lower standard errors than did the models trained on all data. This could be due to the difficulty of trying to incorporate the GFC and the unorthodox interest rate behavior of the COVID-19 era.

4.3.1 National Model

Year	Coef.	Std.Err.	Z	$P > \|z\|$	[0.025	0.975]
2000	2.2	1.05	2.08	0.0371	0.13	4.26
2004	1.7	0.77	2.22	0.0266	0.2	3.21
2008	1.39	0.56	2.48	0.0131	0.29	2.48
2012	1.3	0.46	2.82	0.0048	0.4	2.2
2016	1.35	0.42	3.18	0.0015	0.52	2.18
all-time	1.1	0.37	3.01	0.0026	0.38	1.81

4.3.2 MSA Model

Year	Coef.	Std.Err.	Z	$P > \|z\|$	[0.025	0.975]
2015	1.1	0.26	4.15	0.0000	0.58	1.62
2016	1.15	0.26	4.37	0.0000	0.63	1.67
2017	1.07	0.25	4.21	0.0000	0.57	1.56
2018	0.8	0.22	3.7	0.0002	0.38	1.22
2019	0.85	0.21	4.07	0.0000	0.44	1.26
all-time	0.58	0.18	3.14	0.0017	0.22	0.94

5 Results

5.0.1 National Model

Year	accuracy	precision	recall	F-score	specificity
2000	0.76	0.55	0.5	0.52	0.85
2004	0.75	0.53	0.5	0.51	0.84
2008	0.77	0.54	0.54	0.54	0.85
2012	0.78	0.56	0.56	0.56	0.85
2016	0.75	0.5	0.6	0.55	0.8
all-time	0.75	0.5	0.6	0.55	0.8

5.0.2 MSA Model

Year	accuracy	precision	recall	F-score	specificity
2015	0.65	0.16	0.25	0.19	0.73
2016	0.63	0.16	0.33	0.21	0.68
2017	0.61	0.11	0.33	0.16	0.65
2018	0.67	0.06	0.17	0.09	0.72
2019	0.62	0.07	0.33	0.12	0.65
all-time	0.62	0.07	0.33	0.12	0.65

5.1 Analysis of Results

6 Conclusion

Declarations

6.1 Funding

This research is a part of one author's role as VP of Research and Data Analytics at a Real Estate Private Equity firm.

6.2 Conflict of interest

One author works for a Real Estate Private Equity firm which has ownership interest in many office and multifamily assets throughout the US.

6.3 Availability of data and material

Data available upon request.

6.4 Code availability

Code available upon request.

6.5 Authors' contributions

Each of the authors confirms that this manuscript has not been previously published and is not currently under consideration by any other journal.

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